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Machine learning-based assistance for electrode position validation in tSCS

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Abstract: Spinal cord injury and multiple sclerosis can affect a patient's walking ability and can be accompanied by spasticity. Transcutaneous spinal cord stimulation (tSCS) aims at reduction of spasticity and improvement of locomotion. This work investigates a machine learning approach to evaluate a chosen dorsal electrode position. If the position is classified as unsuitable for therapy, a recommendation for displacement is made. Classified EMG data of the posterior root muscles, evoked by a series of double-stimulation pulses with increasing intensity, and anthropometric data from 18 subjects were used to train a decision tree classifier. An average accuracy of 78% regarding a ground truth algorithm was observed.

I. Introduction

Medical conditions such as spinal cord injury (SCI) or multiple sclerosis (MS) decrease or even inhibit the walking ability of affected patients due to leg paralysis and spasticity. The limitations of movement accompanied by both conditions can severely decrease the quality of life. Transcutaneous spinal cord stimulation (tSCS) can help to reduce spasticity and improve movement control of the lower extremities [2]. Before treatment with tSCS, a suitable electrode position has to be located. Typically, a clinical calibration takes about 7 to 15 minutes [1], when using three to four self-adhesive electrodes for stimulation as well as electromyography (EMG) for reflex measurements (illustrated in Fig. 1).

This procedure is time-consuming and a high amount of material is necessary, which makes the process less appealing and economical. We aim to improve the electrode position validation procedure by placing only one of the electrodes in combination with a classification algorithm. The suggested method assesses if the electrode position is acceptable or should be moved along the rostal-caudal axis to a new position.

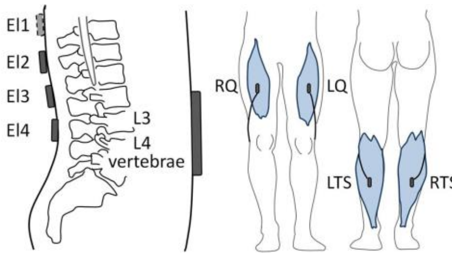

Figure 1: Left: Dorsal electrodes and abdominal counter electrode; right: EMG position quadriceps (Q) and triceps surae (TS).

The assessment is based on a decision tree algorithm regarding muscle reflexes in the EMGs and anthropometric data from healthy individuals and SCI patients.

II. Material and methods

For the machine learning, data sets from 13 healthy subjects (5 females, 8 males, age 30.4 ± 6.8) and five subjects with SCI (2 females, 3 males, age 47.4 ± 12.0) in supine position were used. Five of the healthy and one of the SCI subjects were included twice, whereas the measurement trials took place on different days and with slightly different electrode positions. Therefore, these measurements are treated as obtained from separate subjects. This adds up to 24 trials/subjects. For each trial, either all four or the lower three electrodes from Fig.1 were attached. At each position, double stimulations with an interpulse interval of 50ms were conducted with different current amplitudes. The current amplitudes were increased in steps of 5mA, and the applied maximum varied between subjects based on their personal tolerance (max. 35-80mA). To detect posterior root muscle reflexes, two EMG sensors were placed on each leg, recording the surface activity of the left and right triceps surae and quadriceps muscle group as shown in Fig. 1. For each current amplitude and muscle group, the EMG signal can be labelled as reflex response, no response or muscular response. Based on the occurrence of reflex responses at the different electrode positions, the ground truth algorithm introduced in [1] determines the best position. The lowest current amplitude of the best position which has any reflex response is multiplied by 0.9, to keep the therapy intensity under moto threshold [1]. This current $\hat{I}$ is used for treatment. A total of 82 electrode positions were included. According to the ground truth algorithm, 24 were suitable, 32 too high, and 26 too low on the spine, with reference to the optimal position.

For assessing the suitability of a single electrode position, a decision tree classification was implemented based on the scikit learn Python library [3]. Accordingly, the following three input parameters (features) were defined, inspired by [1]:

- N_{max}: The maximum number of muscles with an observed reflex response after a double pulse stimulation
- *Imbalance*: The number of reflex responses in Qs subtracted by the number of reflex responses in TSs over all stimulation intensities
- $\Delta\hat{I}$: The difference between current amplitude, at which the first reflex is observed, and the expected current amplitude $\hat{I}_{BMI}$ for treatment

$\hat{I}_{BMI}$ is the expected value of $\hat{I}$ based on an observed correlation of a subject's $\hat{I}$ and its body mass index (BMI) (regression coefficient = 0.87). The regression line for calculating $\hat{I}_{BMI}$ uses the values of the healthy subjects.

A two-stage decision tree classification is determined based on input parameters, the Gini impurity as weight function, and the labels of the ground truth algorithm. A first decision tree is trained discriminating between acceptable and unacceptable positions. Then a second tree is trained on all unacceptable positions, which distinguishes whether a position is too high or too low. For both stages, the optimal number of leave nodes is determined by a hyper parameter optimization. The classification performance was evaluated by a leave-one-subject-out cross-validation to assess the generalisation of the proposed algorithm.

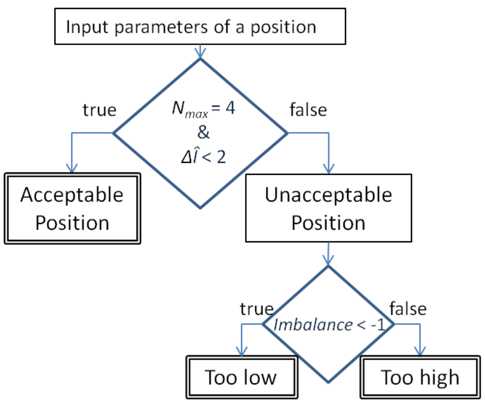

Figure 2: Example of a decision tree from the cross-validation.

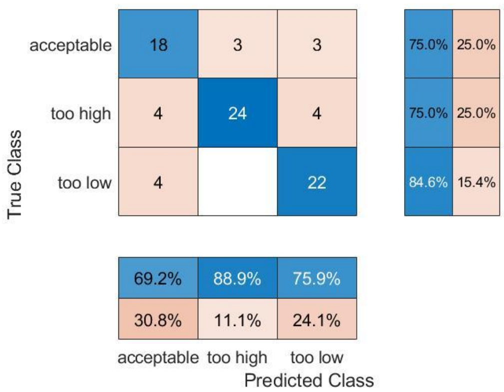

Figure 3: Confusion matrix: True class based on [1], predicted class based on the leave-one-subject-out cross-validation.

III. Results

The determined number of leave nodes is three for the first stage and two for the second stage. An example tree can be seen in Fig.2. Data sets are considered as acceptable if the N_{max} equals four and $\Delta\hat{I}$ is smaller than 2mA. Therefore, an acceptable electrode position can only be found if reflexes occur in all four muscles (N_{max} = 4). At stage two the positions are labelled as "too high" if the *Imbalance* is above or equal -1 and "two low" otherwise. The tree structure was stable for the cross-validation, only the parameter threshold of $\Delta\hat{I}$ varied slightly. Considering the results shown in Fig. 3, it can be seen that in the cross-validation 64 of the 82 samples were classified consistent with the ground truth. This equals an accuracy value of 78%. 14 out of 18 mistakes result from the first stage. Since electrode position 3 is optimal in 13 of the 18 subjects, it is used as the starting position for the proposed method. Using the decision tree, the correct position is identified directly or after one change of position according to the algorithm's recommendation in 15 of the 24 subjects. In 5 subjects all positions are classified as unacceptable. If the ground truth algorithm is used in these special cases, the optimal position will be found as well. In the remaining 4 subjects a non optimal position is classified as acceptable, which yields an error of 16.7%.

IV. Discussion and Conclusions

The implemented classifier has a lot of potential to minimize the preparation time prior to the tSCS treatment. In some cases different electrodes are selected than suggested by the ground truth algorithm. However, if all four muscle groups show reflexes and the therapy current is close to $\hat{I}_{BMI,}$ it might still be a decent second choice. The introduced procedure and thresholds, especially of stage one, including the correlation assumption between the BMI and the current amplitude should be validated with a larger data set.

Author's Statement

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