An Active Learning Based Prediction of Epidural Stimulation Outcome in Spinal Cord Injury Patients Using Dynamic Sample weighting

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Introduction

- Recent studies suggest that epidural stimulation of the spinal cord could increase the motor pattern both in motor and sensory complete spinal cord injury (SCI) patients [1, 2].
- Choosing the optimal epidural stimulation variables, such as the frequency, intensity, and location of the stimulation, significantly affects maximal motor functionality [3].
- This paper presents a novel technique using machine learning methods to predict the motor functionality of a SCI patient after epidural stimulation.
- We suggest a committee-based active learning method [4] to reduce the number of clinical experiments required.
- This paper also introduces a novel method to dynamically weight the results of different experiments based on neural networks to create an optimal estimate of the quantity of interest.
- The proposed algorithm can be applied to a wide range of experimental settings in which several noisy samples of a quantity of interest are available in conjunction with features that can predict that quantity.

Experimental Setup

- A 28 years old male chronic SCI ASIA-C patient enrolled in the current study.
- A 32 contact paddle (Coverage X32, Boston Scientific Corporation) was implanted in the dorsal aspect of the cervical spine.
- The contacts in each row are stimulated together. Also, we have explored the frequencies of 5, 30, 60 and 90 Hz, and intensities between 1 mA to 6 mA.
- The data used in this study consists of 29 different experimental sessions, which were conducted during a 15 week period.
- Prior to each session, experimental configurations (i.e., frequency, intensity, and location) were selected based on decisions by a human expert.

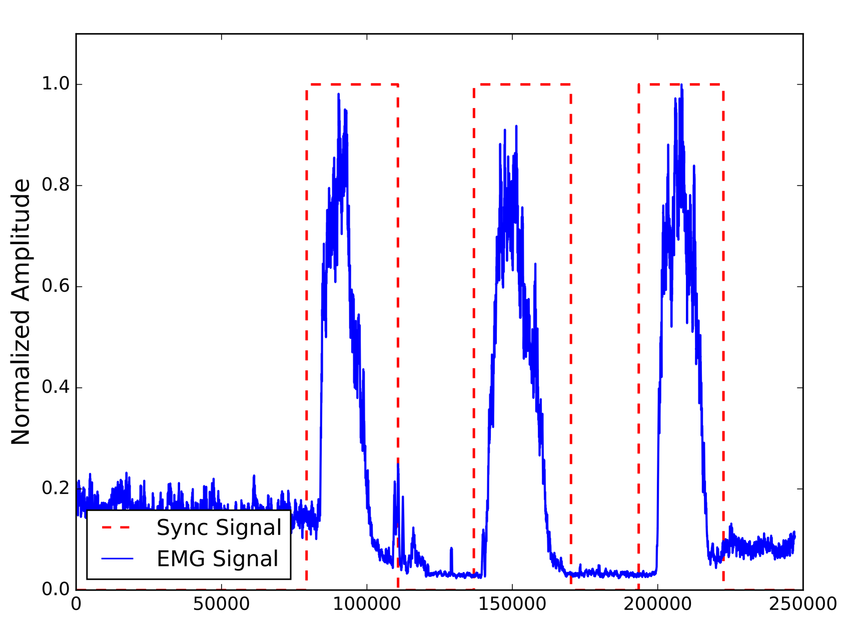


Figure 1: Using the synchronization signal to divide the EMG signal to three portions, each corresponding to a trial within the experiment.

Methodology

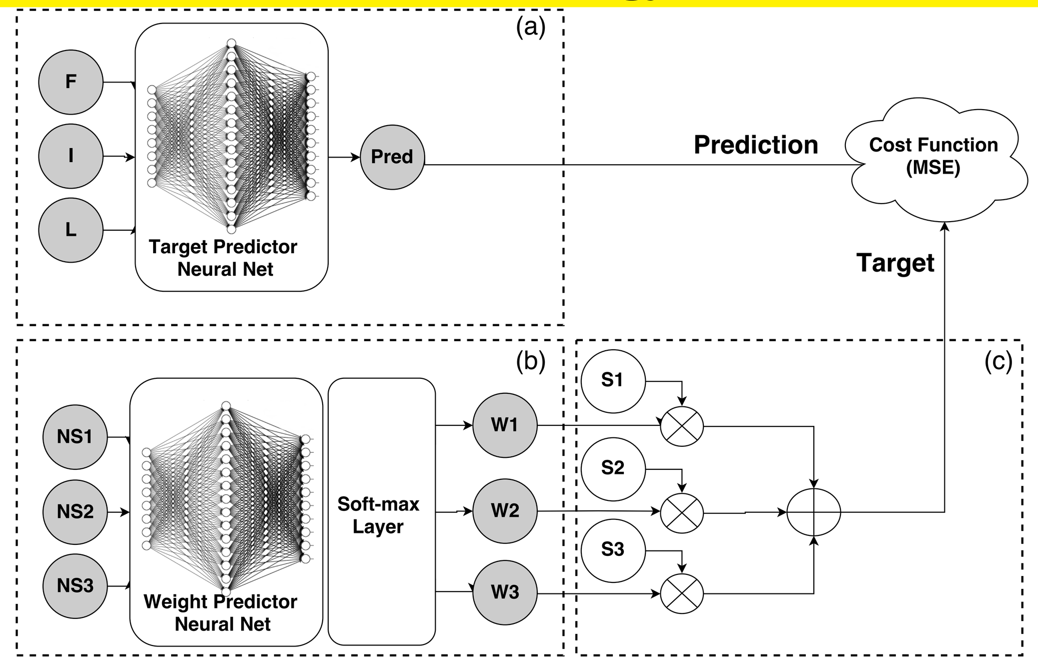


Figure 2: The proposed neural network architecture. The network can be separated to (a) the outcome predictor, (b) the dynamic weight predictor, and (c) the weighted average calculator.

I. Preprocessing

- Basic signal processing pipeline for the EMG and Sync signals including: decimation, full-wave rectification, and median filtering.
- Separating the preprocessed EMG signal to three parts, each representing a single hang-grip MVC.
- Calculating scores for each window:

$$Score = \frac{Score_{stim} - Score_{baseline}}{Score_{baseline}} \tag{1}$$

II. Calculation of Target Values

- We need to calculate a single target score from these scores as the outcome of each experiment.
- Many scores were contaminated with noise or the subject was distracted or did not completely cooperate.
- Here, it is proposed to use a weighted average to calculate the target values, while the weights are determined using a predictor model which dynamically predicts the appropriate weightings for each trial score (see Fig. 2).

III. Prediction of Target Values

- RBF-kernel support vector regression (SVR)
- Model hyper-paramters were selected based on a 10-fold exhaustive grid search cross validation ($C = 15, \epsilon = 0.01, \gamma = 0.001$).

IV. Increasing the Learning Efficiency

- Using active-learning methods to reduce the amount of required training data.
- A committee of eight SVRs models was trained using bootstrap aggregating (each time selecting 90% of training data randomly with replacement).
- The variance of committee member predictions were used to find samples with the highest disagreement.

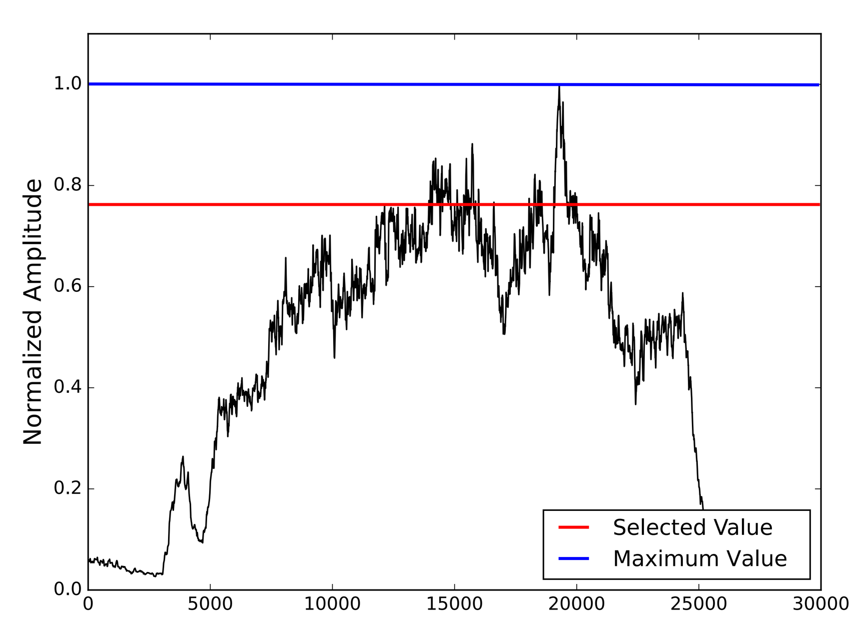
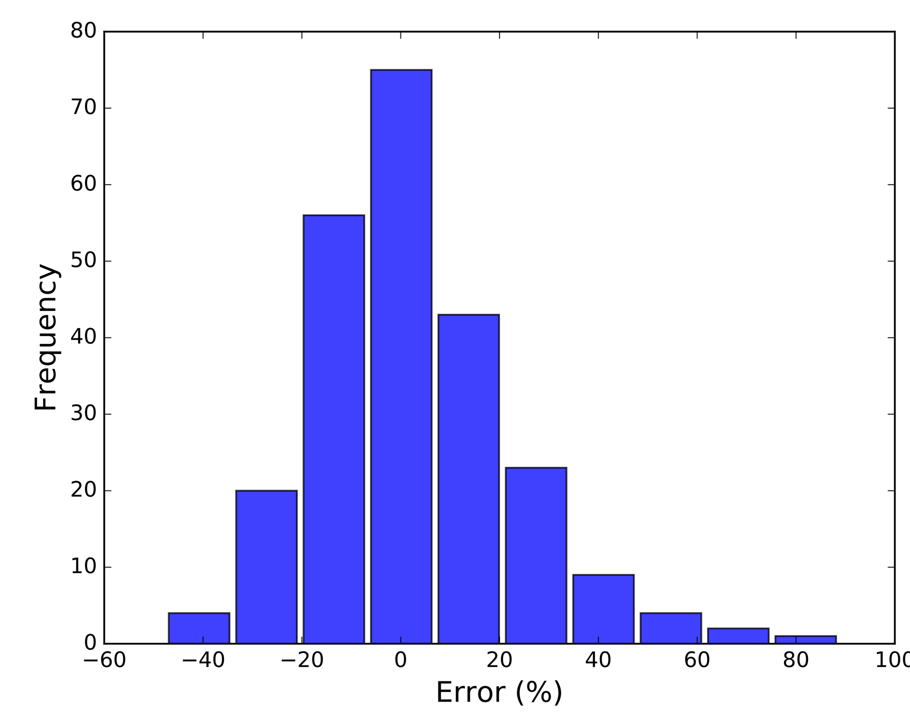


Figure 3: Score calculation in a single EMG portion.

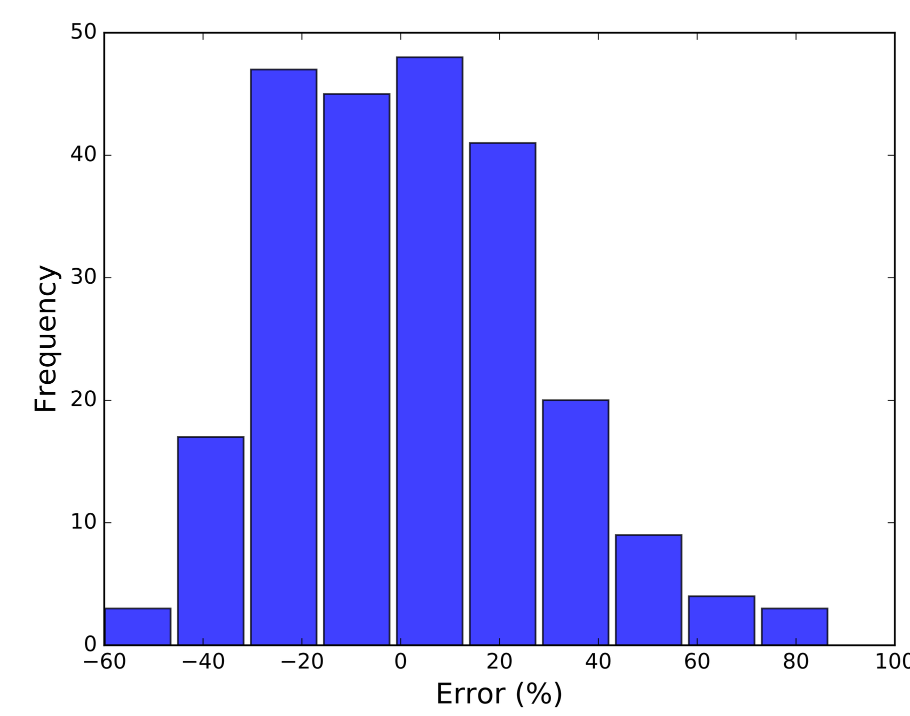
Results

Table 1: Comparison between the proposed dynamic score weighting approach and mean/median approaches.

	Mean	Median	Proposed Approach (NeuralNet)	Proposed Approach (SVR)
MAE (%)	21.07	21.63	20.01	**15.23**
STD (%)	26.65	27.38	26.12	**20.25**
r	0.55	0.57	0.60	**0.64**



(a)



(b)

Figure 4: Histogram of errors using: (a) Dynamic Weighting and SVR regression (b) Mean and SVR regression.

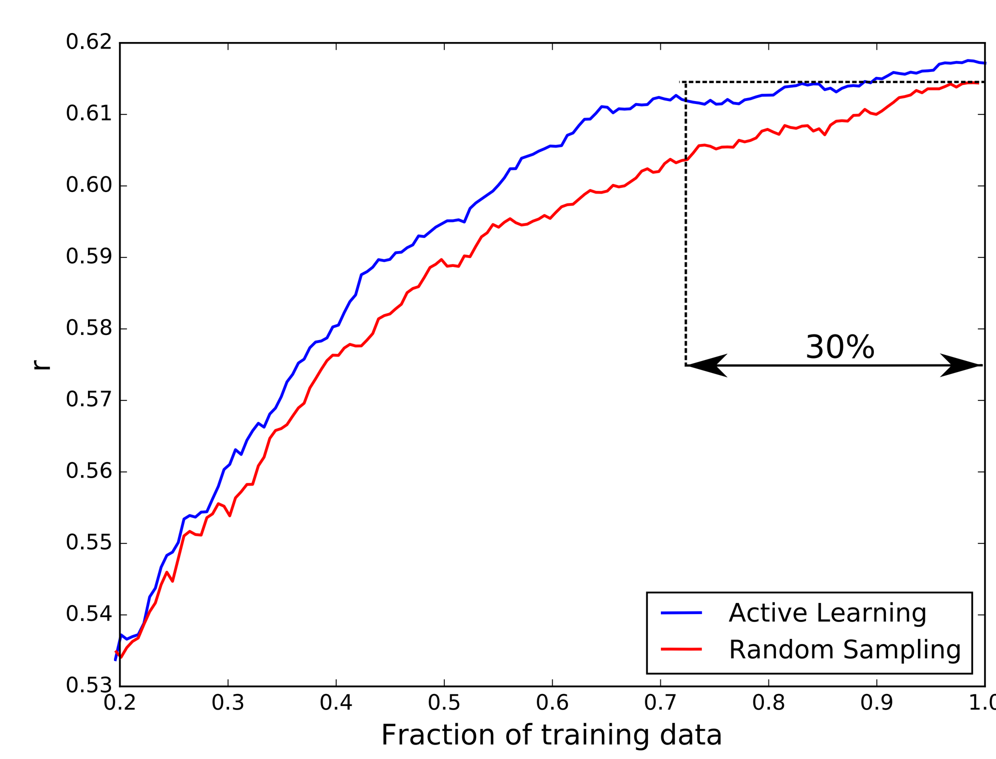


Figure 5: The performance of active learning compared to random sampling in terms of r-value.

Conclusion

- We have presented an efficient approach for the prediction of epidural stimulation outcomes.
- An active learning method was introduced to reduce the number of costly clinical experiments.
- This paper also presented a novel algorithm based on neural networks for the dynamic prediction of averaging weights corresponding to several measurements.
- The proposed method was capable of predicting the epidural stimulation outcome with the MAE of about 15%, while the active learning method was successfully employed to reduce the number of required clinical experiments by about 30%.

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