PRESENTING AUTHOR'S NAME & RESEARCH TITLE

Corey Pew, PhD, MS

Comparison of sEMG and HDEMG for Automatic Human Activity Recognition

PURPOSE/BACKGROUND

Surface electromyography (sEMG) sensors are able to detect the small electrical signals of muscle contractions through the skin. These can be used to help determine motion intent for clinical/biomedical applications [1]. While sEMG has seen wide application in upper limb prosthetic devices there has been little clinical implementation for lower limbs [2]. This is because sEMG signals can be unreliable during daily activity and for lower limb devices even small errors can cause injurious falls. Newer, high-density (HD) sEMG sensor have recently become available that have the potential to improve the reliability of sEMG as a control signal for lower limb prostheses. The objective of this research was to compare Standard (SD) and HD sEMG signals using intent recognition with machine learning algorithms [3] and determine if HDsEMG had the potential for improved prosthesis control.

MATERIALS & METHODS

Seven participants were recruited for an experimental study to relate motion of the lower limbs to varying sEMG inputs. Participants performed activities of daily living (ADL) including stair ascent/descent, straight walking, ramp ascent/descent, left/right turning, and squats. Placement of sEMG sensors is shown in Figure 1. Sensors were placed in both optimal locations and 1 cm displaced distally to simulate the effects of socket movement. Both SD and HD sEMG sensors were placed in all configurations. Data, labeled by activity was then associated to the varying sEMG to assess different machine learning classifiers to determine if classification of activity varied by sensor type and position. First, several time domain and frequency domain features which were extracted which included: Integrated EMG, modified mean absolute value, simple square integral, variance, absolute value of the 3rd, 4th, and 5th temporal moment, root mean square, average amplitude change, difference absolute standard deviation value, zero crossing, myopulse percentage rate, Wilson amplitude, slope sign change, mean absolute value slope, Autoregressive coefficients, cepstral coefficient, mean frequency, median frequency, peak frequency, mean power, total power, the 1st, 2nd, and 3rd Spectral moments, frequency ratio, and variance of central frequency [4]. Initial results indicated that time domain feature group attained highest accuracy. In addition, a randomized tree was used to further refine feature selection and determine the most appropriate feature set [5].Window size for feature was set to 480 samples, equal to the average stride time for the participant with an overlap of 470 samples. Varying classifiers were tested for their overall accuracy to identify activity type from sEMG signals alone. This included Random Forest, Support Vector Machine, adaboost, LDA, MLP, and autosklearn [6,7] with hyperparameters tuned via random search. HDsEMG sensor data contained information from 32 electrodes (16 for the extensor and 16 for the flexor muscle) as compared to single input from SDsEMG. To accommodate the varying data electrodes were paired together and 16 different models were trained to determine classifications from each data pair. Then a majority voting is used to determine the final a prediction.

RESULTS

Data collection has been completed, but data analysis is ongoing. Table 1 provides results for a single, representative.

Table 1:Classification report for sEMG and HDEMG data for subject3 in unseen data

	SEMG		*HDEMG*	
Sensor placement	optimal	displaced	optimal	displaced
Accuracy	68%	70%	67%	62%
# of samples	37	37	33	26
Model name	RF	Autosklearn	lda	lda

DISCUSSION/CONCLUSION

Accuracy for SDsEMG data was slightly higher than the for HDsEMG data. One reason may be the volume of the dataset for training models. Number of samples in the Test Data (which is 30 percent of total data) indicates that the models were trained with more samples therefore they could attain higher accuracy. In general, we expect to get higher accuracy when the sensor placement is in its optimal position. We can see that this is the case for HD data however for SD data the displaced sensor attained the accuracy which is similar (a little higher than) to the optimal sensor placement trial, a Result that we hope has more clarity as we process data from other individuals.

In this research we developed two pipelines that automatically perform classification for SDsEMG and HDsEMG data. While other works combine different sensors such as IMU, Gyroscope, EMG to perform classification, this research only focused on the contribution of EMG data. Another challenge of this research was the number of classes for prediction (13 different activities) which is greater than the average number of classes (5 activities) that models in the literature are developed for classification.