OPTIMIZING PATTERN RECOGNITION-BASED CONTROL FOR PARTIAL-HAND PROSTHESIS APPLICATION

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Introduction

- Although myoelectric prostheses have recently become available to partial-hand amputees [1], current control methods are limited.
- Pattern recognition of surface electromyography (EMG) acquired from the extrinsic hand muscles in the forearm could provide improved control.
- EMG generated from wrist movement degrade hand grasp pattern recognition performance. We employed the following techniques to mitigate this degradation:
  - Incorporating intrinsic hand muscle EMG
  - Training a classifier in different wrist positions and during dynamic movements [2]
  - Increasing window length [3]
  - Reducing the number of grasps available to the classifier
- Pattern recognition control of hand grasps, which accounts for wrist movement could lead to increased device adoption and use in daily activities.
- **Objective:** Supplement a myoelectric pattern recognition system with these techniques and evaluate improvements in classifier performance.

Methods

Data Collection

Subjects

- Recruited 9 able-bodied subjects

Hand-Grasps

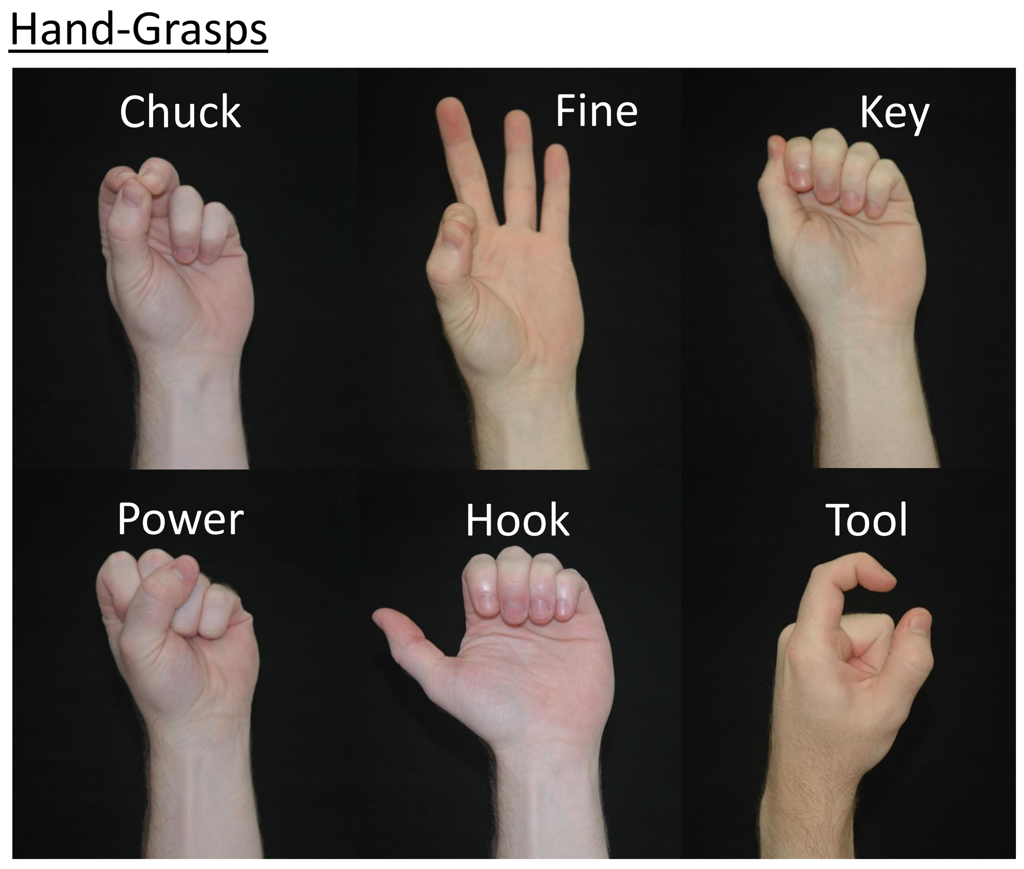

Figure 1. Grasps performed during experiment.

Electrode Placement

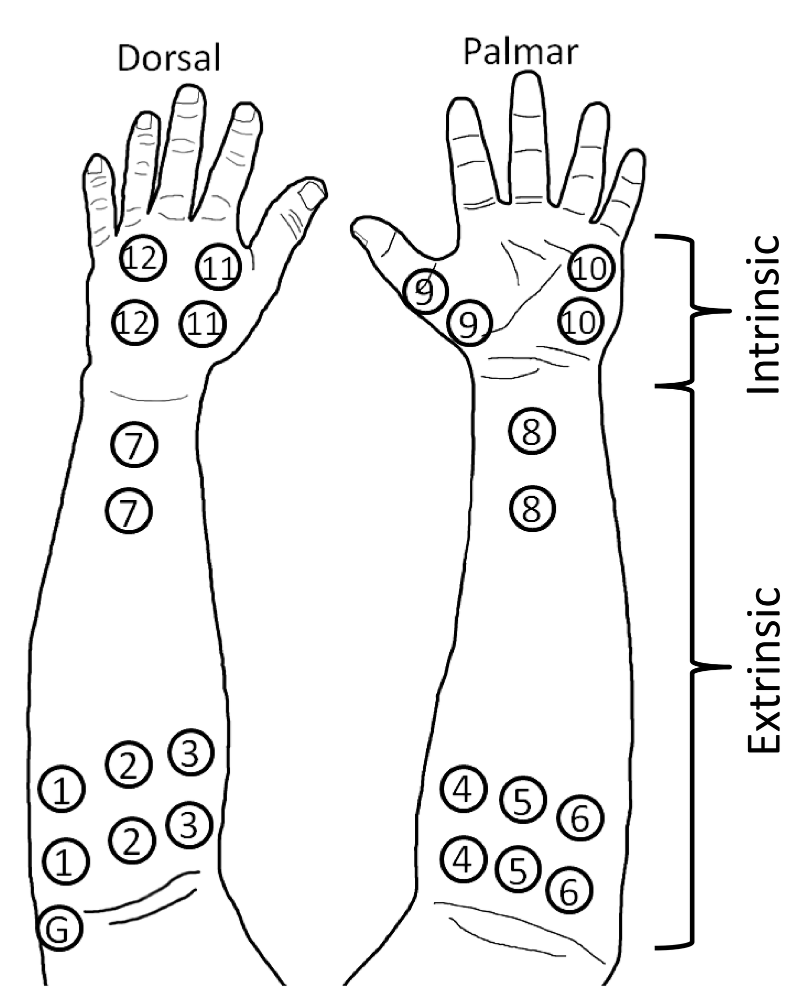

Figure 2. Electrode placement. Electrodes 1-8 cover extrinsic muscles, and electrodes 9-12 cover intrinsic muscles.

Wrist Positions

1. With wrist in the neutral position and six other wrist positions (static wrist data)
2. While moving wrist along each of its three degrees of freedom (dynamic wrist data)

Offline Classifier Evaluation

Classification Algorithm

- Linear discriminant analysis [4]

Muscle Group Training Sets

1. Extrinsic muscle EMG
2. Intrinsic muscle EMG
3. Extrinsic and Intrinsic muscle EMG

Wrist Training Sets

1. Neutral wrist data
2. Static wrist data
3. Dynamic wrist data
4. Static and dynamic wrist data

Window Lengths

- Feature extraction windows [3]: 100, 200, 300, 400, 500 ms

Grasp Modes

- Grasp Selection
  - Classes: *no movement*, *hand open*, or one of *N* hand-grasps
  - Total of *N*+2 classes
  - Classifier tested with static data set
- Grasp Maintenance:
  - Classifier selects from *no movement*, *hand open*, or *hand close*
  - Total of 3 classes
  - Classifier tested with static and dynamic data sets

Statistics

- 2-fold cross validation
- 2-way ANOVA

Results

Table 1. Classification error with different combinations of training methods and electrode placements, during grasp selection and grasp maintenance. Tests performed using a 250ms EMG window and with 6 grasps available to the classifier. Classifiers tested against data collected in all seven static wrist positions (selection), and in all positions and during all movements (maintenance).

Electrode Placement		Training Method: Neutral Wrist Position	Variable Wrist Positions	Dynamic Wrist Movements	Variable Wrist Positions + Movements
Grasp Selection					
	Extrinsic	52.74%	17.29%	34.17%	20.89%
	Intrinsic	32.97%	16.50%	28.39%	19.20%
	Extrinsic + Intrinsic	36.72%	3.83%	15.16%	5.89%
Grasp Maintenance					
	Extrinsic	22.19%	8.21%	6.87%	6.29%
	Intrinsic	11.75%	5.50%	4.38%	4.33%
	Extrinsic + Intrinsic	15.05%	3.00%	1.98%	1.49%

- Training classifier in multiple static wrist positions or during dynamic movements significantly reduced classification error ($p<0.001$)
- Collecting from both extrinsic and intrinsic electrode locations significantly reduced classification error ($p<0.001$)

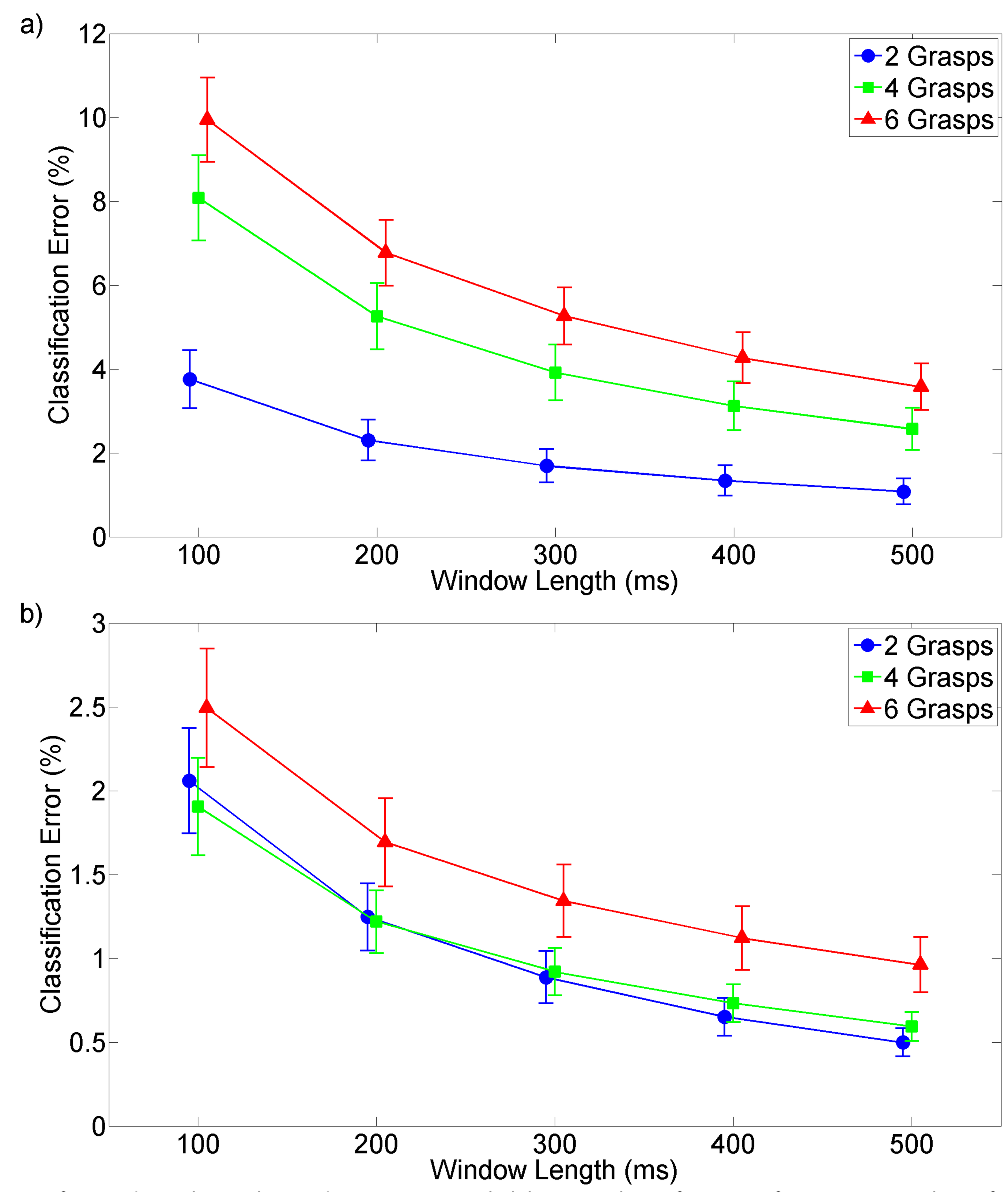

Figure 3. Effect of window length and grasps available on classifier performance. Classifiers used all extrinsic and intrinsic EMG, and trained in all positions and during all movements. (a) Classification error during grasp selection, tested against data collected in all seven static wrist positions. (b) Classification error during grasp maintenance, tested against data collected in all positions and during all movements.

- Longer window lengths yield lower classification error, but provide smaller incremental improvements as window length increases ($p<0.001$)
- Adding more grasps to a classifier increases classification error ($p<0.001$)
- Longer window lengths provide greater performance improvement when more grasps are available during grasp selection ($p<0.001$)

Conclusions

- Training a classifier in conditions similar to those encountered during everyday use provides improved system performance via reduced classification error. When extrinsic EMG are supplemented by intrinsic EMG, this error is also minimized.
- Analyzing longer windows of data becomes more vital as more grasps are made available to the classifier.
- With these additional techniques, low classification error rates can be achieved while still permitting the use of the wrist for daily activities.

Acknowledgements

This work was supported by the Department of Education, NIDRR RERC grant number H133E130020, NIH grant number T32HD7418, and NICHD grant number 1F31HD078092-01.

References

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