sEMG Hand and Wrist Movement Classification: Evaluating QUANT Features

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Introduction

Surface electromyography (sEMG) is a method to detect and record the electrical activity of muscles. Robust sEMG-based control is crucial for prosthetic hand function, yet roughly one-third of upper-limb amputees abandon sEMG prostheses due to limited control reliability.

- In response, we propose using QUANT, a interval feature extraction method that computes sorted signal values (quantiles) from fixed-length time intervals.
- We aim to assess whether these features, paired with machine-learning classifiers, can improve movement-classification accuracy for prosthetic control applications.

Dataset

- We used the publicly available NinaPro DB7 dataset [1].
- The DB7 dataset contains sEMG measurements recorded from 20 subjects.
- 12 sensors were placed around the forearm: eight sensors equally spaced around the radiohumeral joint and four sensors on the flexor digitorum, extensor digitorum, biceps, and triceps.
- Subjects performed two exercises: 17 finger/wrist movements and 23 grasping and functional movements.

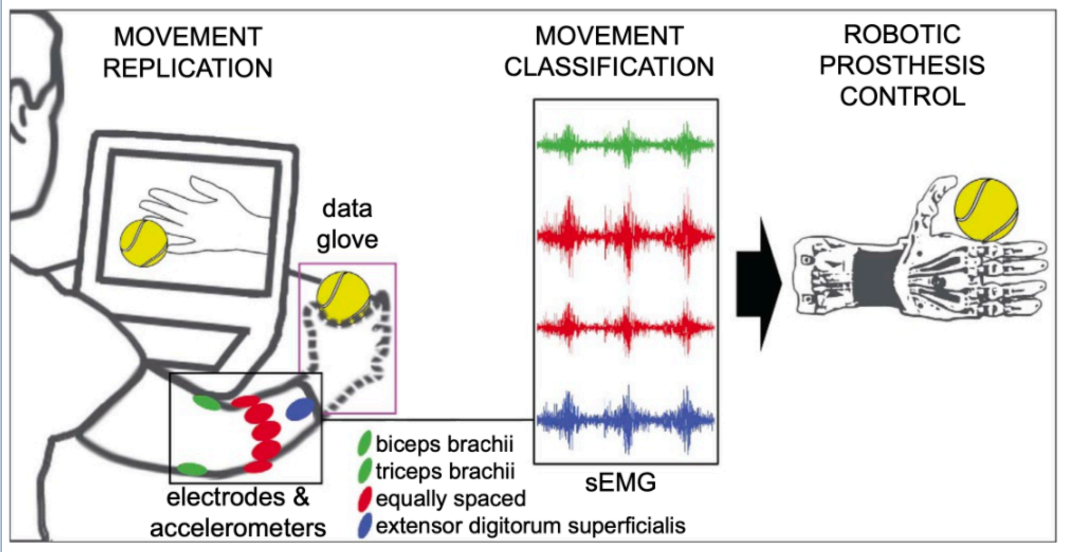


Fig 2. Acquisition procedure [1].

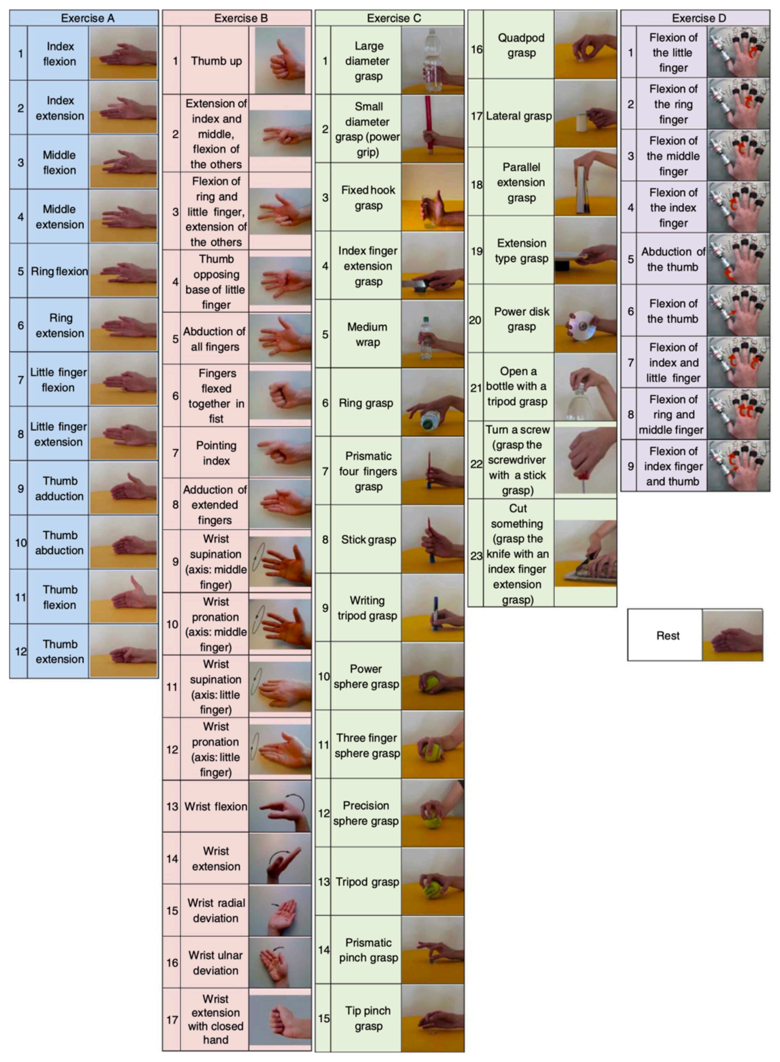


Fig 3. Hand movements. Performed exercises: B, C [1].

Methods: Feature Extraction

- A set of representative quantiles from each sorted interval formed the features.
- Each sEMG time series was divided into fixed intervals at multiple depth levels, with depth controlling the number of features.
- The interval mean was subtracted from every second quantile, such that we compute features representing both the distribution of value in the interval and the distribution of the values in the interval relative to the mean
- As the interval length decreases, the intervals approximate the original time-series values more closely.

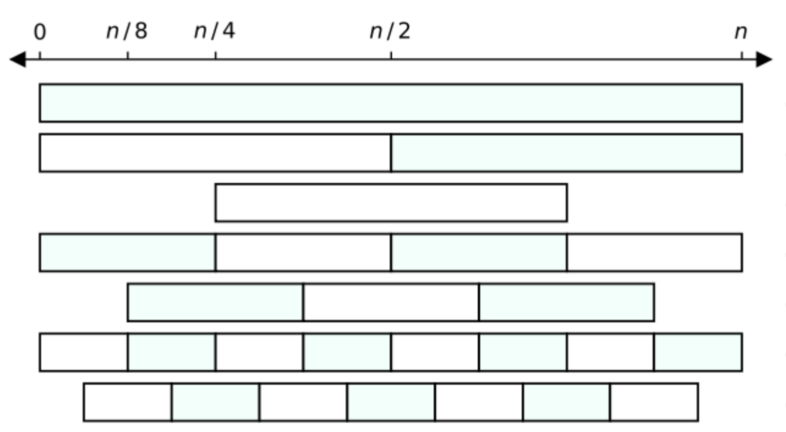
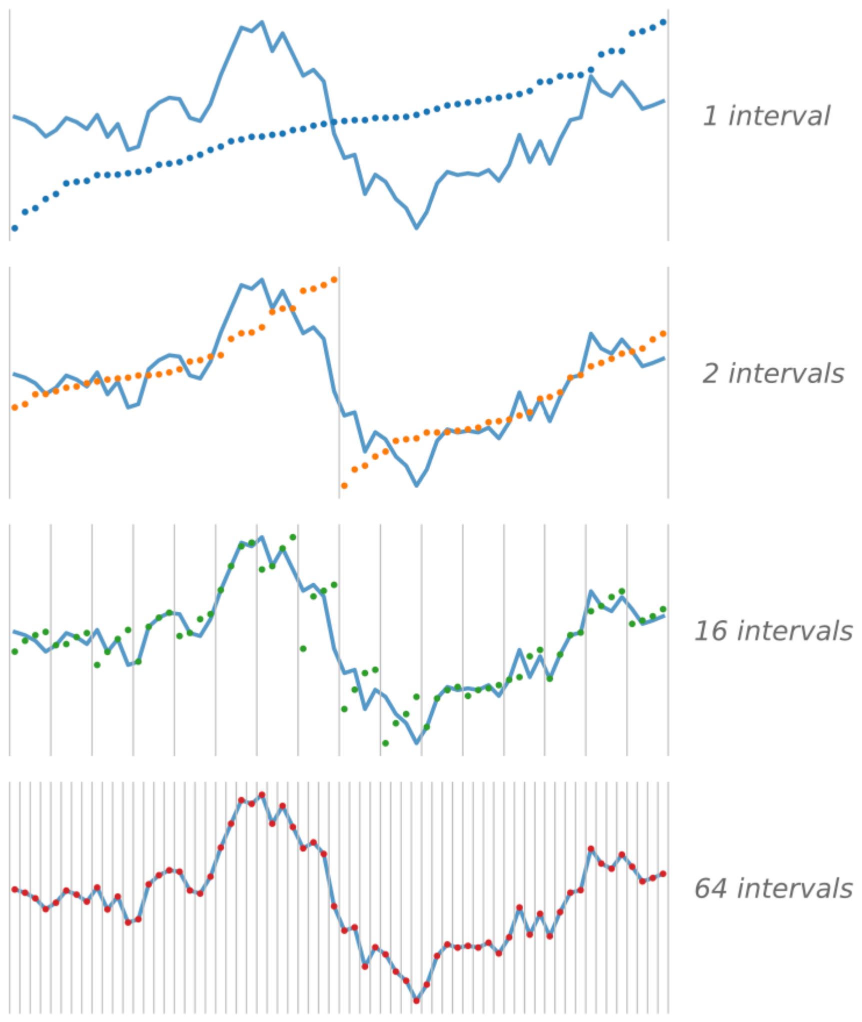


Fig 4. An illustration of the set of intervals for depth of $d = 4$, including 'shifted' intervals for $d > 1$ [2].



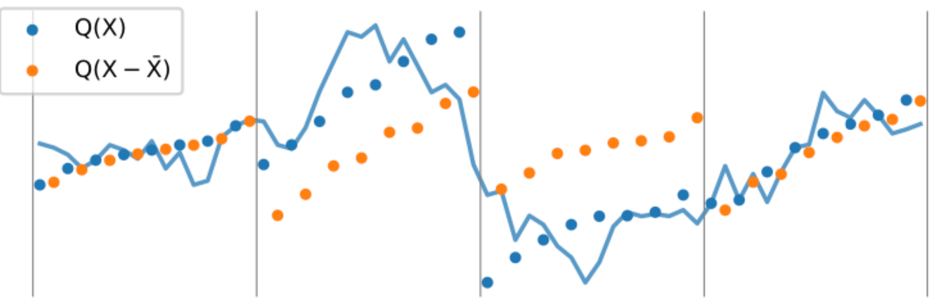


Fig 5. An illustration of quantiles drawn from interval of length $n / 4$ [2].

Fig 6. Sorted values for interval of decreasing length [2].

Methods: Classification

- We evaluated two classifiers: Extremely Randomized Trees (ExtraTrees) and Ridge. Both used 30 resamples.
- For the ExtraTrees classifier, we varied "max features," which is the maximum number of features ExtraTrees considers when splitting a node. ExtraTrees used 200 estimators.
- We performed subject-specific classification: for each subject and resample, each class contributed 4 training trials, 1 validation trial, and 1 test trial.
- We also tested cosine similarity features with ExtraTrees.

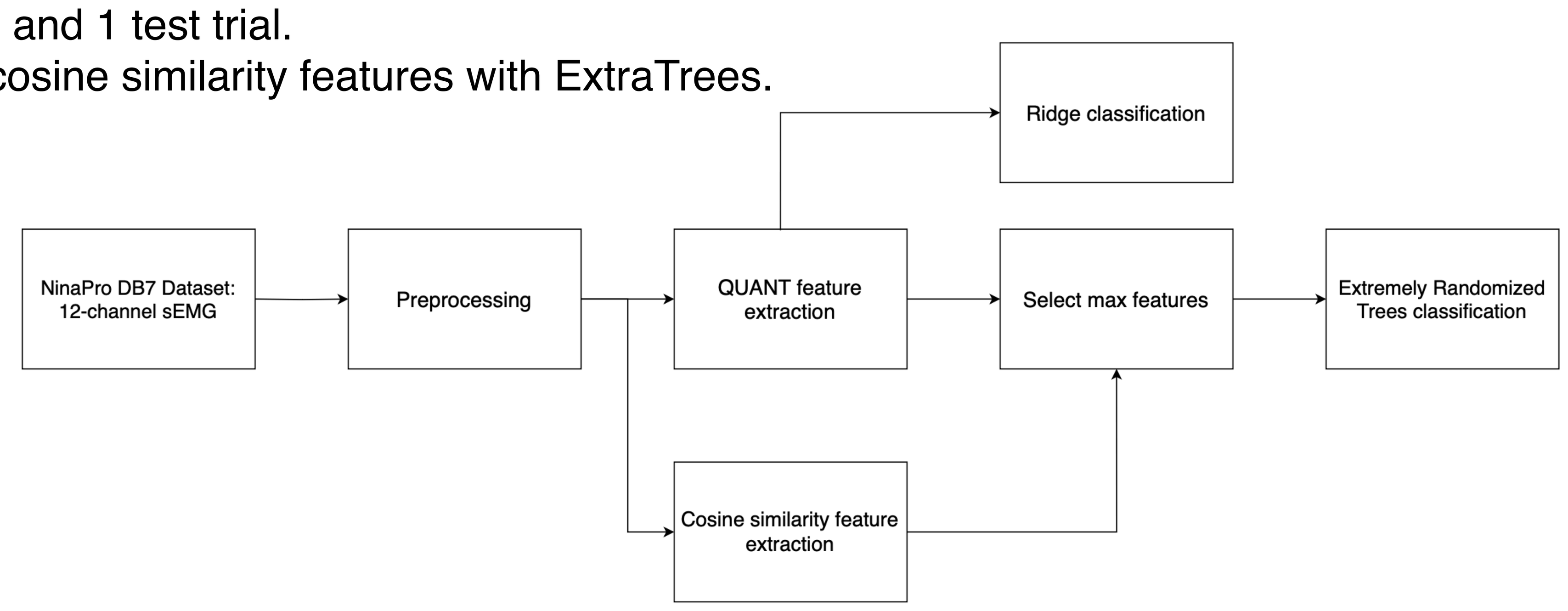
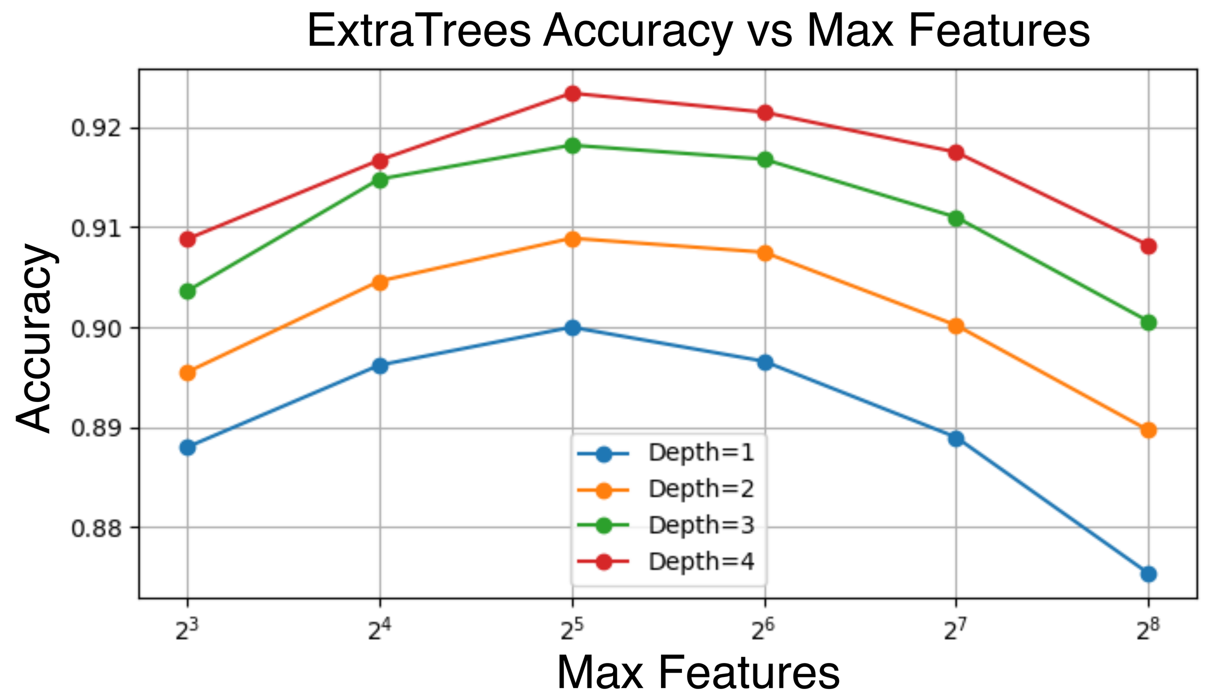
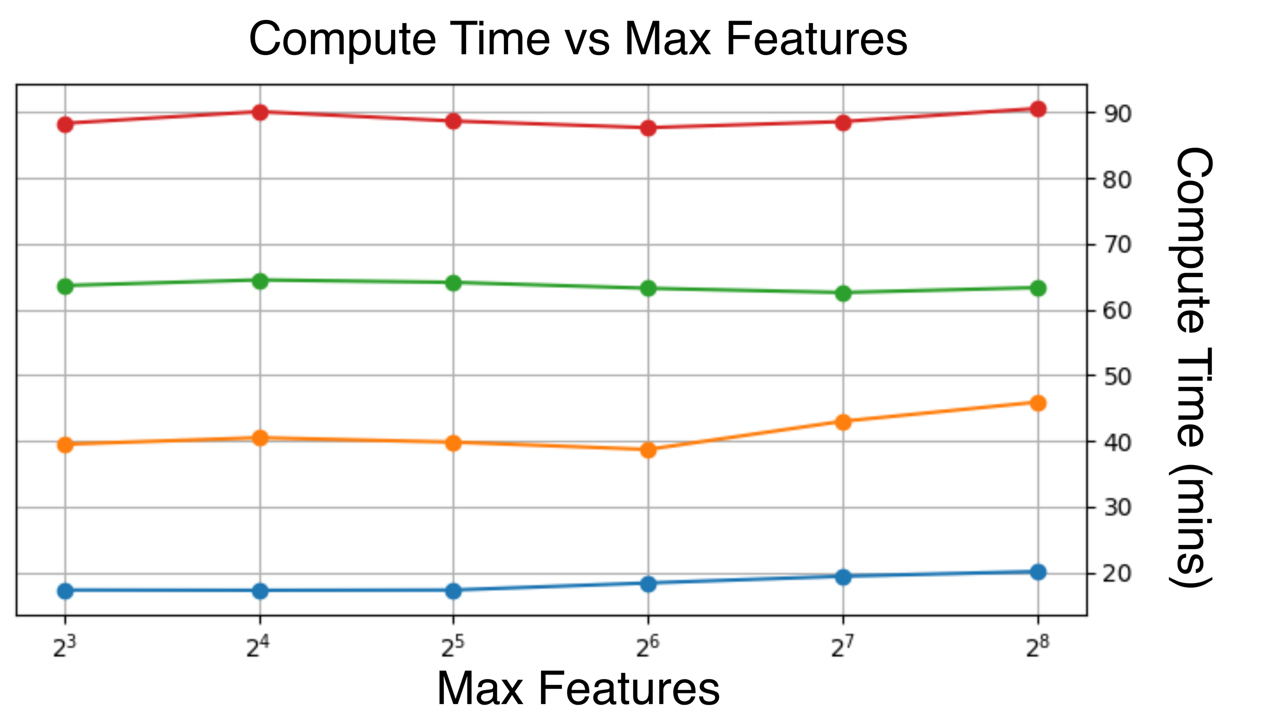


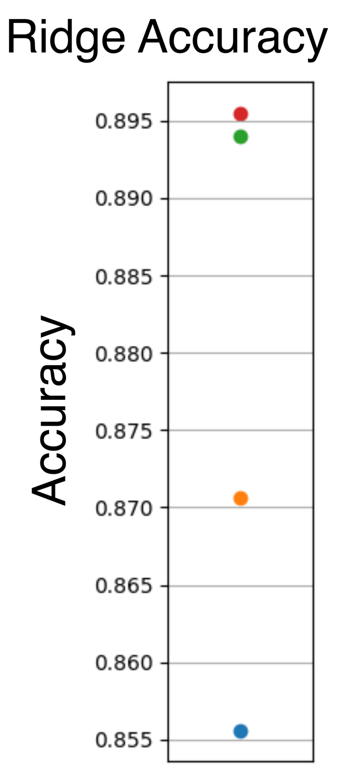
Fig 7. Algorithm Flow

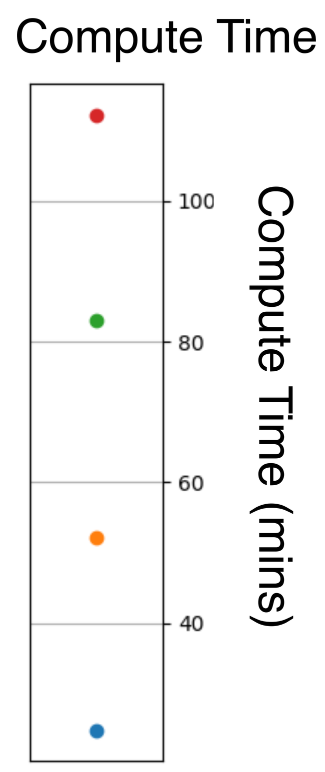
Results

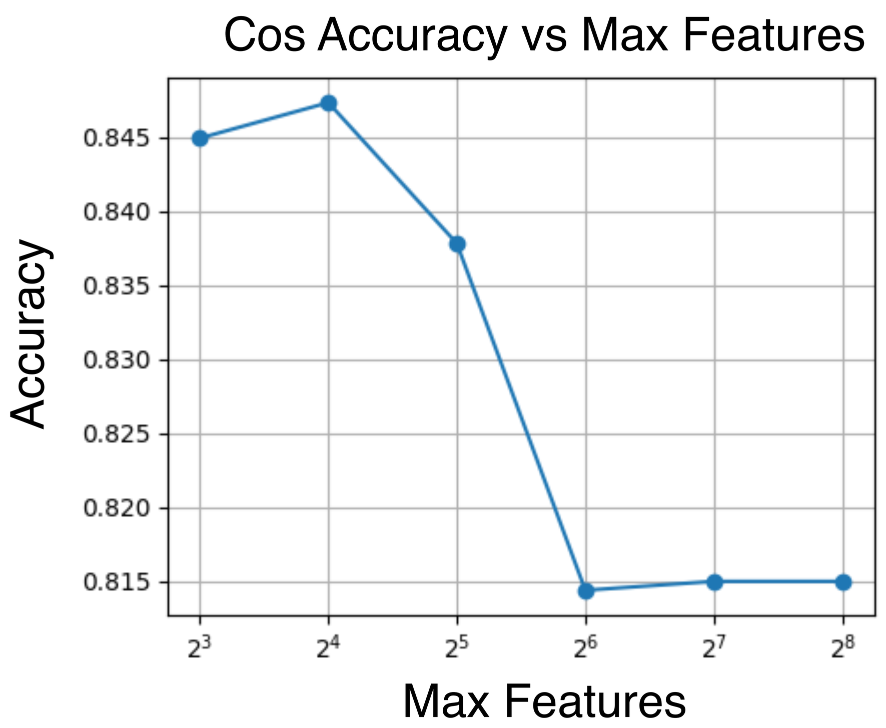
- QUANT features with the ExtraTrees classifier had test accuracies ranging from 0.8468 ± 0.0304 at depth 1 (138,108 features) to 0.9234 ± 0.0249 at depth 4 (845,964 features).
- QUANT features with the Ridge classifier had test accuracies ranging from 0.8554 ± 0.0388 at depth 1 to 0.8956 ± 0.0397 at depth 4.
- Cosine similarity features (66) with ExtraTrees yielded test accuracies ranging from 0.8473 ± 0.0463 with max features set to 16 to 0.8150 ± 0.0500 with max features set to 1024.
- All experiments were conducted on an 8-core CPU laptop.

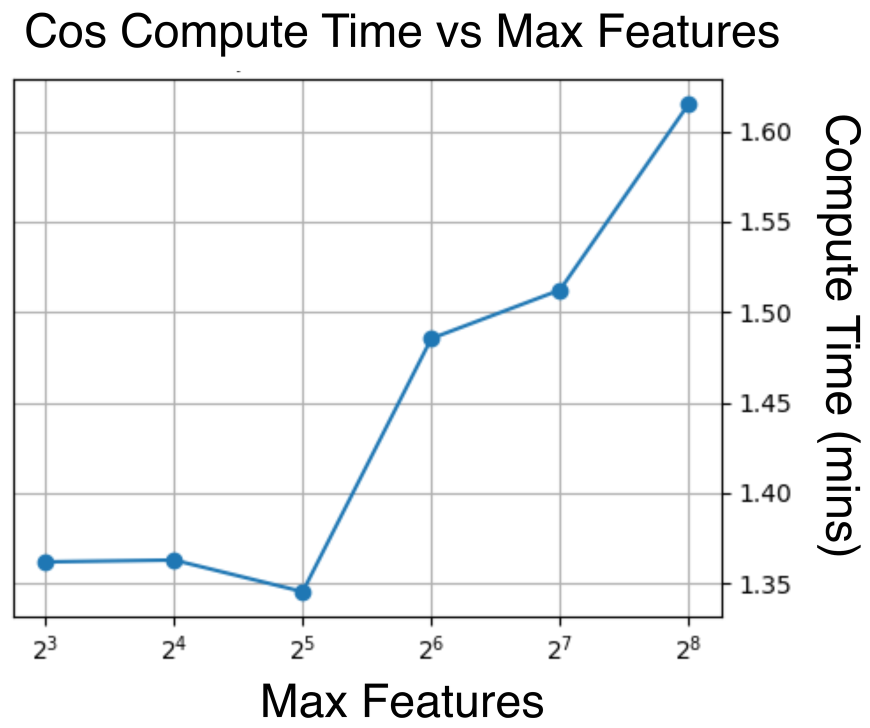












Conclusion and Future Work

- QUANT delivers state-of-the-art accuracy for multi-class sEMG and is computationally lightweight.
- Cosine similarity features with the ExtraTrees classifier delivers moderate-accuracy and low runtime, a suitable alternative for quick prosthetic calibration or low-resource settings.
- Practically, a prosthetic controller could use QUANT features with the ExtraTrees classifier where resources allow, to maximize accuracy, or fall back to cosine features alone when speed and simplicity are paramount.
- Improving dependable sEMG pattern recognition along this accuracy–latency continuum can reduce control frustration, potentially lowering prosthesis rejection and enhancing user quality of life.

References

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