# sEMG Hand and Wrist Movement Classification: Evaluating QUANT Features

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## Abstract

Surface electromyography (sEMG) enables non-invasive monitoring of muscle activity and is central to developing intuitive control strategies for upper-limb prostheses. However, limitations in classification reliability contribute to high abandonment rates among users. Deep learning approaches have achieved state-of-the-art accuracy but remain computationally demanding for real-time, on-device deployment. In this study, we evaluate a lightweight alternative based on QUANT, a minimalist interval feature extraction method that represents signal distributions via quantiles computed from fixed-length segments of multichannel sEMG. Using the publicly available NinaPro DB7 dataset (20 subjects, 40 distinct hand and wrist movements), we extracted QUANT features at varying depths and assessed classification performance with Extremely Randomized Trees (ExtraTrees) and Ridge Classifiers. QUANT features achieved high accuracy, with ExtraTrees yielding test accuracies up to 92.34% ± 2.49% at depth 4, and Ridge achieving up to 89.56% ± 3.97%. A clear trade-off emerged between accuracy and runtime: the highest-accuracy configuration (845,964 features) required 88.6 minutes of total compute time, while a more efficient setup (138,108 features) achieved ~90% accuracy in 17.3 minutes. Cosine similarity features provided a rapid, low-dimensional alternative, yielding moderate accuracy (~85%) with runtimes under two minutes. These findings demonstrate that QUANT balances state-of-the-art accuracy with computational efficiency, making it suitable for resource-constrained, real-time prosthetic applications. Depending on clinical priorities, prosthetic systems could deploy QUANT with ExtraTrees to maximize accuracy or rely on cosine features for fast calibration. By supporting robust, adaptable sEMG classification, these approaches may improve prosthesis usability and reduce device rejection.


**Keywords:** surface electromyography (sEMG); prosthetic control; time-series classification; QUANT; quantile-based features; ExtraTrees classifier; Ridge classifier; computational efficiency; NinaPro DB7

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## 1. Introduction

Surface electromyography (sEMG) is a non-invasive technique for recording muscle electrical activity and is widely used for human-machine interfaces in rehabilitation and prosthetics. Robust sEMG-based control is crucial for advanced prosthetic hand function, yet roughly one-third of upper-limb amputees abandon myoelectric prostheses due to limited control reliability and intuitiveness. Improving the classification of sEMG signals can enhance the responsiveness and user acceptance of prosthetic devices. While deep networks have recently delivered high accuracy, their computational complexity and hardware requirements limit real-time, on-device use. We therefore propose a novel, lightweight approach to classify hand and wrist movements from multichannel sEMG using quantile-based time-series features. In particular, we evaluate QUANT, a minimalist interval feature extraction method that computes sorted signal values (quantiles) from fixed-length time intervals. Our objective is to assess whether these features, paired with machine-learning classifiers, can improve movement-classification accuracy for prosthetic control applications.

## 2. Materials and Methods

We used the publicly available NinaPro DB7 dataset [1]. The DB7 dataset contains myoelectric measurements recorded from 20 subjects (Fig. 1). Twelve Delsys Trigno 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. sEMG signals were sampled at 2 kHz. Subjects performed two exercises: 17 finger/wrist movements and 23 grasping and functional movements.

We extracted quantile-based interval features using QUANT [2]. Each sEMG time series was divided into fixed intervals at multiple depth levels, with depth controlling the number of features. A set of representative quantiles from each sorted interval formed the features, summarizing the distribution of signal amplitudes. We varied the depth to explore the feature space. We evaluated two classifiers: (i) Extremely Randomized Trees (ExtraTrees), and (ii) a Ridge Classifier (Fig. 2). For the ExtraTrees classifier, we varied "max features," which is the maximum number of features ExtraTrees considers when splitting a node. We also tested cosine similarity features with ExtraTrees to measure inter-channel similarity.

We performed subject-specific classification: for each subject and resample, each class contributed four training trials, one validation trial, and one test trial. We used 30 resamples for ExtraTrees and Ridge. ExtraTrees used 200 estimators, and Ridge used "alpha" equal to 1. We measured classification accuracy and standard deviation for each subject and recorded computational time for feature extraction and classifier training and prediction.

## 3. Results

QUANT-based interval features classified 40 hand/wrist movements from sEMG with high accuracy. 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) (Fig. 3a). 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 (Fig. 3b). 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 (Fig. 3c). ExtraTrees consistently yielded higher classification accuracy than Ridge on QUANT features. Cosine similarity features alone resulted in modest accuracy.

## 4. Conclusion

We observed a trade-off between classification accuracy and computational efficiency. All experiments were conducted on an 8-core CPU laptop. The highest-accuracy (0.9234) configuration, 845,964 QUANT features with ExtraTrees, had an 88.64-minute runtime for all 20 subjects. Of that total runtime, transform training took 85.76 minutes, 2.08 minutes on fitting the classifier, and 0.71 minutes on prediction. However, a similar classification accuracy (0.90) configuration of only 138,108 QUANT features with ExtraTrees had a 17.28-minutes compute time for all 20 subjects. Transform training took 15.94 minutes, 0.92 minutes on fitting the classifier, and 0.35 minutes on prediction. Using 66 cosine similarity features with ExtraTrees yielded a 1.36-minutes runtime for all 20 subjects. Transform training took 0.33 minutes, 0.69 minutes on fitting the classifier, and 0.27 minutes on prediction.

## 5. Discussion

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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**Figure 1:** Movement Types (figure taken from [3])

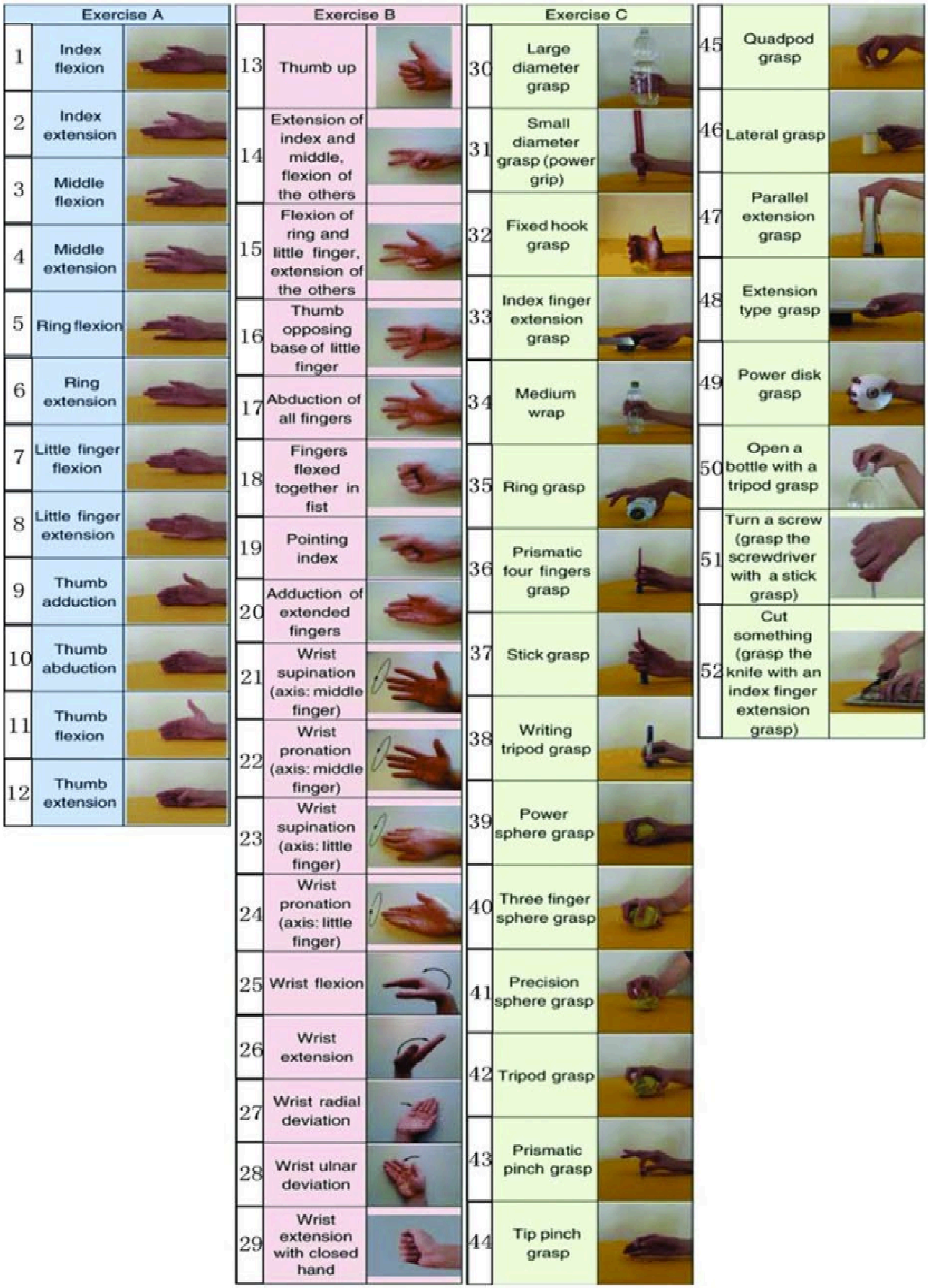

**Figure 2:** Algorithm Flow

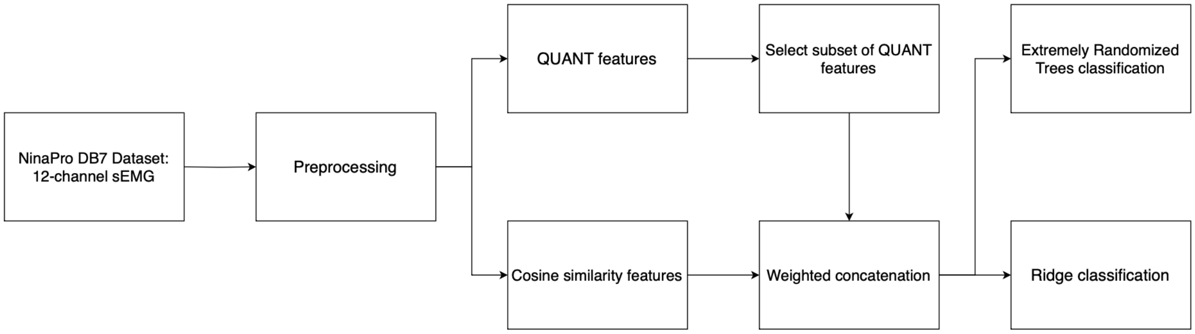


**Figure 3a:** QUANT Features ExtraTrees Classifier Test Accuracy Versus Max Features

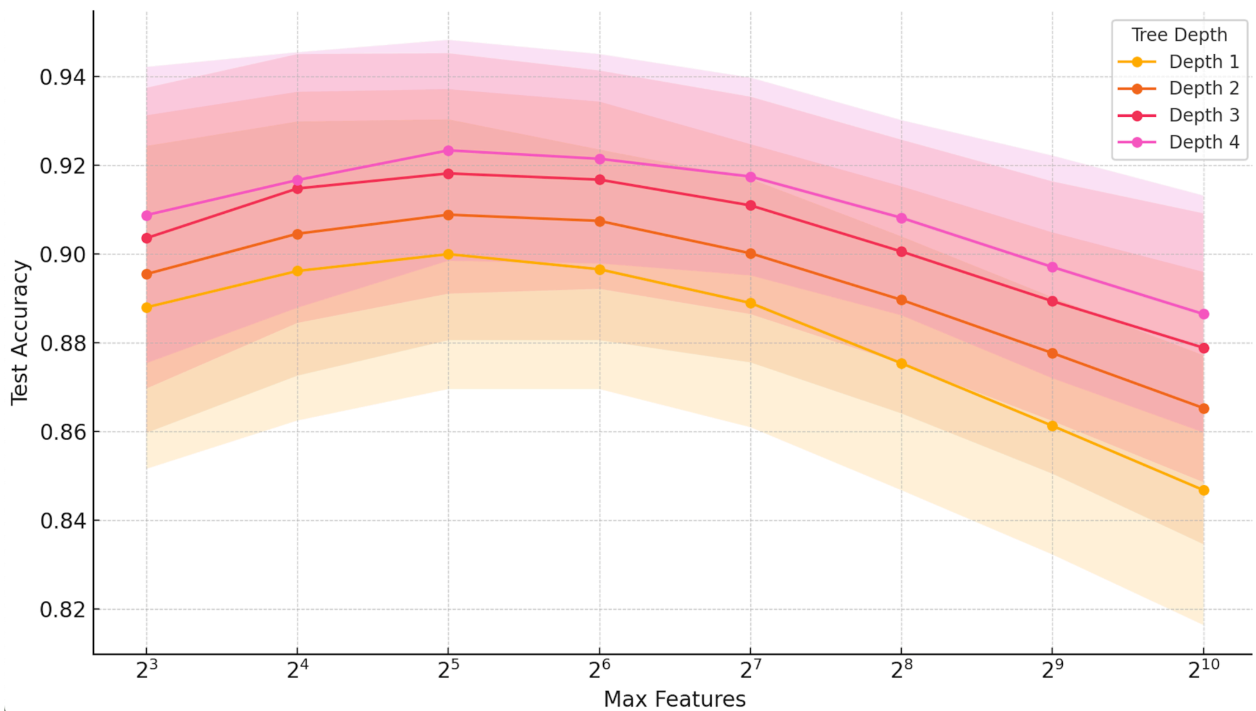

**Figure 3b:** QUANT Features Ridge Classifier Test Accuracy Versus Depth

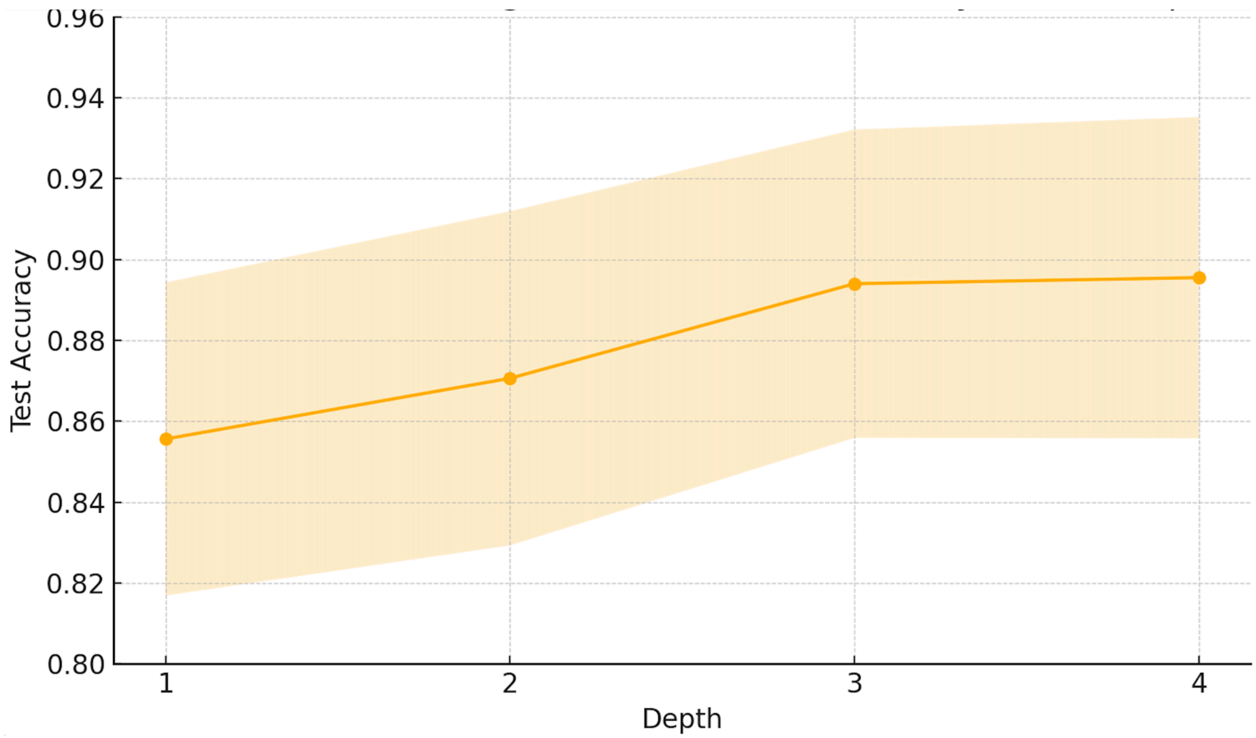


**Figure 3c:** Cosine Features ExtraTrees Classifier Test Accuracy Versus Max Features