# PATTER RECOGNITION MYOELECTRIC CONTROL CALIBRATION QUALITY FEEDBACK TOOL TO INCREASE FUNCTION

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## ABSTRACT

Pattern recognition control for upper-limb myoelectric prostheses is growing in clinical acceptance. Furthermore, powered prostheses are becoming increasingly complex, especially with the growing popularity of multi-articulating hands [1]. With a larger available motion set, requiring a larger number of patterns of muscle activity, complications can arise. Calibration feedback to rate the ability to control each available motion and provide tips for subsequent recalibration is highly beneficial in these cases. Here, a novel algorithm for determining calibration quality is presented.

## INTRODUCTION

Since commercialization in late 2013, many individuals with upper limb loss and limb difference have benefitted from pattern recognition control for myoelectric prostheses [2]. Since its initial release, many software tools have been developed and deployed, primarily to assist prosthetists in fitting and properly integrating the pattern recognition control system. For instance, a clinician assistant tool provides an interface for clinicians to communicate directly with a support representative by submitting a package including the most recent set of calibration data for troubleshooting and further analysis; a real-time signals analysis tool alerts users to EMG signals that are possibly unreliable (primarily the result of poor skin-electrode contact or signals that are too high and clipping); and a practice tool provides an environment to further explore pattern recognition control with two games: a posture matching game based on the Target Achievement Control (TAC) test and a proportional control game [3].

All of the aforementioned software-based tools have proven to be invaluable. However, there has remained a need to provide clear and concise feedback describing the pattern recognition calibration quality to the user. No clinically focused tool has been developed to rate the quality of calibration data for each available motion. Technical descriptions such as classification error rates have been traditionally used, but they do not adequately explain the underlying cause of poor calibration, such as late contraction initiation, or a contraction performed in the incorrect sequence. A properly designed tool can automatically analyse calibration datasets and provide clear, concise feedback and guidance on ways to modify subsequent recalibration to improve prosthesis control. Without this tool, diagnosing the cause of unsatisfactory prosthesis control, with the exception of EMG signal quality issues such as electrode lift-off or saturation, is difficult, leaving clinicians and users to make educated guesses as to why control may not be as expected. Furthermore, users are left to an unstructured and highly experimental approach to determine preferred calibration techniques. This sometimes requires iterating through a calibrate-and-check-control process multiple times before identifying a user-specific method to achieve satisfactory prosthesis control. Some users may feel uncomfortable with such an unstructured approach to finding a preferred calibration technique, possibly becoming fatigued from the experimentation process or even possibly becoming frustrated with suboptimal control. A software feedback tool should considerably reduce the time necessary to achieve high-functioning control.

## CURRENT APPROACH

Improving the quality and character of muscle contraction patterns presented during calibration of a pattern recognition control system improves the capability to form patterns that can be accurately recognized by the pattern recognition system. Preliminary evidence suggests that this also leads to improved functional control of the prosthesis over a multiple week home-trial [4, 5].

Some common approaches to improve the richness of EMG signal pattern information, such as varying contraction strength or increasing the differentiation between contraction patterns, can make a significant difference in prosthesis control and thereby greatly reduce frustration as well as the support burden on clinicians [6, 7].

The current commercial pattern recognition myoelectric control system uses an open-ended calibration format where the only mechanism to validate the control is to attempt to control the movements of the prosthesis. This is an ad-hoc approach that can be discouraging when the resulting control is suboptimal. Without instruction feedback, as an example, users often increase muscle contraction intensity in the case of unsatisfactory control, further obscuring the ability of the controller to decipher intended movements. Providing

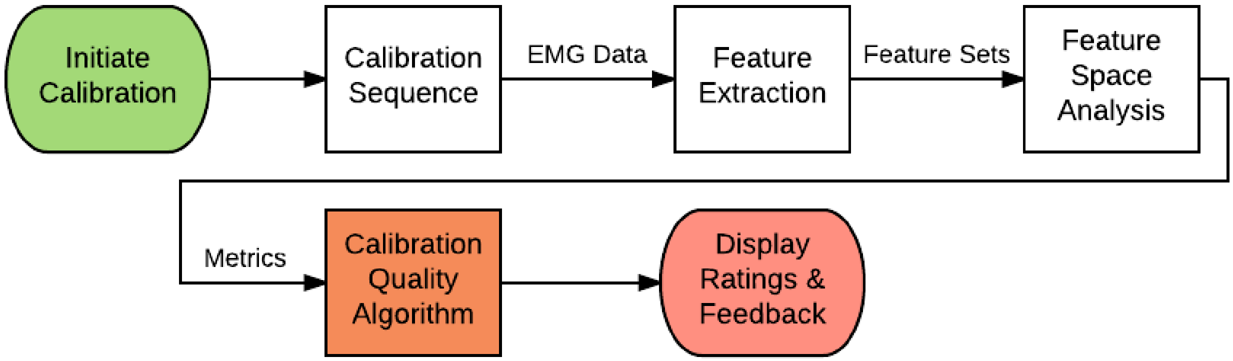


**Figure 1:** Calibration quality software tool flowchart

assistive feedback can positively reinforce the user experience with pattern recognition as users can be informed of motions that are likely to be suboptimal, the likely underlying causes, and guidance on corrective actions. Furthermore, without a mechanism for feedback, it is not always clear to pattern recognition users in their own environment when it is appropriate to contact their clinician for controls assistance if they are struggling.

## CALIBRATION QUALITY SOFTWARE TOOL

### Background

The need for a calibration quality software tool has been identified through various forms of qualitative feedback from clinicians who have fit pattern recognition control systems and current users. Unsatisfactory prosthesis control has caused users to contact their prosthetist or support representative for assistance and guidance for control improvement. Providing greater autonomy in identifying ways to improve prosthesis control serves to increase prosthesis function and acceptance.

### Purpose

The purpose of the calibration quality software tool is to inform the user of the pattern recognition control system in ways that promote both early-stage controls learning and continued functional growth. The intent of the tool is to analyse each available motion and provide clear, concise feedback messages to instruct users in ways to perform subsequent recalibration differently to improve prosthesis control.

### Description

There are 3 major aspects of the calibration quality software tool: 1) the underlying algorithmic processes to evaluate character and quality of users' pattern recognition EMG data; 2) the determination and presentation of the quality rating for each functional motion class; and, 3) the autonomous formation of the instructional feedback messaging to the user (hints for improvement). Figure 1 shows a high level flowchart of the calibration quality input, data processing, algorithm, and output to the software user interface.

### Calibration Quality Assessment

The calibration quality tool algorithm primarily analyses users' EMG data after the data has been represented in feature space (Figure 1) – a critical component of pattern recognition, whereby EMG data is modelled in a lower-dimensionality subspace. Two Mahalanobis distance-based metrics, Separability Index (SI) and Repeatability Index (RI), are computed using the feature set data of each available class (equations from Kim et al. 2016) [8-10].

The Mahalanobis distance between two class feature sets is computed as

$$D_M(X,Y): \sqrt{(\mu_X - \mu_Y)^T \tilde{S}^{-1} (\mu_X - \mu_Y)} \tag{1}$$

where $\mu_X$ and $\mu_Y$ are the means of class $X$ and $Y$, and $\tilde{S}$ is the weighted covariance matrix between class $X$ and $Y$, which is computed as

$$\tilde{S} = \frac{n_X}{N} S_X + \frac{n_Y}{N} S_Y \tag{2}$$

where $n_X$ and $n_Y$ are the number of feature sets of class $X$ and $Y$, and $N$ is the total number of feature sets across both classes. Repeatability Index is computed as

$$RI: \frac{1}{r} \sum_{k=1}^{r} D_M(X_r, X_t) \tag{3}$$

where $r$ is the number of times EMG data was collected during calibration for the class, $X_r$ is the feature sets of the $r$th class collection, and $X_t$ is the cumulative feature sets across all EMG data collections for the class. A smaller value of RI indicates greater consistency of the muscle contraction pattern. Separability Index is computed as

$$SI(j) = \min_{i=1,\dots,j-1,j+1,\dots,N} D_M(X_i, X_j) \qquad (4)$$

where the SI of class $j$ is the minimum Mahalanobis distance between motion class $j$ and all other available classes. A larger value of SI indicates greater distance between class $j$ and the nearest neighbouring class.

Quantitative metrics are produced, internal to the algorithm that represent the timing and quantity of EMG contraction data provided by the user during calibration. This detects a multitude of potentially problematic issues in the calibration data and combines the issues, based on level of significance and likelihood to introduce functional difficulties. The resulting metric is a score from 1-5, that is mapped to a 5-star rating system.

### Quality Rating

The primary element for reporting calibration quality per functional motion class is a 5-star rating system. This common standard is generally understood where a 5-star rating is of highest quality and 1-star is of lowest quality. This approach is designed to immediately draw user's attention to lower quality ratings and provide natural encouragement for them to review the 'tips' aimed at improving the rating.

### Informative Feedback

As potentially problematic issues are detected in the calibration data, resulting in a sub-perfect score, a subset of known messages are presented to the user. These messages are short, informative tips created to correct the detected issue during subsequent recalibrations. Each type of detectable and reportable issue is accompanied by a generic statement within the algorithm and the presentation of the messages is via the software interface immediately following calibration. Examples of the categories of these messages include: "Motion A is very similar to Motion B. Consider X to improve muscle pattern separation"; "No EMG data was detected for Motion C. Consider making stronger contractions for C or be sure to contract when prompted.", and; "Motion D is highly variable. Attempt to discover the most repeatable muscle contraction pattern."

## CONCLUSION

Previously, no clinically focused software tool was available to provide feedback to the user to describe the quality of the data used to calibrate a pattern recognition controller. Rather, empirical observation of prosthesis control was required to determine if calibration data was adequate for satisfactory control. The automated procedure presented in this contribution provides a structured framework to provide clinically focused feedback to the user. The resulting "pocket assistant" style tool will be especially beneficial to new users who are attempting to calibrate a pattern recognition for the first time. Initial feedback from beta-users has been positive and the messages provided to the users is continually being expanded.

## SIGNIFICANCE

Pattern recognition control of upper-limb prostheses is growing in clinical acceptance. Further improvements to the calibration scheme improve the clinical viability of pattern recognition control in comparison with conventional amplitude-based control approaches.

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