# OPTIMAL SELECTION OF TIME SERIES COEFFICIENTS FOR WRIST MYOELECTRIC CONTROL BASED ON INTRAMUSCULAR RECORDINGS

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*Abstract*- **The Davies-Bouldin cluster validation technique has been utilized to determine the optimal time series parameters (model, order and number of coefficients) to be used in a myoelectric pattern recognition system based on intramuscular recordings.**

**The data used in our longitudinal study were recorded intramuscularly (4 muscle channels) from an amputee subject over three different experimental days. During the recording sessions, the subject performed 4 wrist movements (pronation, supination, wrist flexion, wrist extension) in a way that was intuitive to her. The time series coefficients obtained from the EMG data (from AR, MA, and ARMA modeling) were used for generating feature spaces with 4 classes (1 per movement). The results showed that the optimal parameters didn't differ substantially (AR, order 4, 2 coefficients) for those obtained for other type of movements and surface EMG recordings. The use of the Davies-Bouldin technique during the analysis produced important information about the separability and consistency of the data across different days.**

***Keywords* - Myoelectric control, EMG, intramuscular electrodes, pattern recognition, time series, cluster validation, Davies-Bouldin index.**

## I. Introduction

Multifunctional myoelectric control usually entails cumbersome operation and time consuming training. Throughout the years, different pattern recognition techniques and EMG feature spaces have been evaluated with the purpose of solving the two above-mentioned problems. Some of the most widely used features have been based on time series coefficients derived from autoregressive (AR), moving average (MA), and/or autoregressive-moving average (ARMA) models [2,3]. The rationale for the use of time series coefficients is based on the relationship between coefficients and the EMG frequency content. Likewise, frequency content is movement dependent due to changes on the motor units populations involved in performing different movements. Because of computational convenience [2], the preferred model type and number of coefficients utilized with surface EMG has been AR with order 3 or 4. Nonetheless, some investigators [1] have claimed that time-series modeling of EMG signals should not be considered static or invariant because the spectral behavior of EMG data is dependent on the specific muscle, contraction level, and limb function. However, their efforts revealed that the best model representing surface EMG was still AR with order 4. Because of the differences in our study (wrist movements, intramuscular EMG, EMG feature extraction performed at the contraction's onset as opposed to extraction during sustained contraction), we believe that the results from former studies may not be applicable to our problem. Thus, we performed an analysis to identify the optimal time-series parameters. With this purpose we utilized the Davies-Bouldin cluster validation technique [4]. This crisp cluster validation technique presents highly desirable characteristics to solve the problem at hand: (1) it performs an evaluation based on the geometrical characteristics of the feature space (it identifies compact and well-separated partitions of the feature space), and (2) it has reduced sensitivity to cluster outliers [5]. In addition, other authors [6, 7] have successfully applied the Davies-Bouldin index to perform comparisons between feature spaces based on EMG data.

## II. Methodology

### *A. Experimental protocol and pre-processing*

The subject was a female (age 33) presenting a below-elbow amputation of her left arm (non-dominant hand) and strong phantom limb sensation. The subject never used a prosthesis since the time of the amputation (13 years before the experiments).

A pair of coiled wire electrodes for bipolar recording was inserted with 2cm tip separation into each of the following muscles: (1) Pronator Teres, (2) Supinator, (3) Flexor Carpi Radialis, (4) Extensor Carpi Radialis. During a period of 30 days, the electrodes remained chronically implanted and, within that period, recording sessions were performed on 12 different days. In our study we used data obtained during the last 3 experimental sessions (i.e., the $10^{th}$, $11^{th}$, $12^{th}$ sessions). The subject was seated facing a computer display that executed the animations of the movements to be evaluated (Fig.1). For each given movement, the subject was requested to follow the animations of the hand while contracting her residual muscles during 4 blocks of exercises (25 trials each). The EMG signals were amplified (between 1000 and 10000 times) and bandpass filtered (10Hz to 1kHz) before being sampled at 2kHz. This sample rate was selected due to the bandwidth of intramuscular recordings (1kHz).

For computational efficiency, we segmented the data into separated files that contained at least 4 trials. We ran an onset-detection algorithm on the trials contained in these files until we obtained the following: (session 10) 51 onsets per movement, (session 11) 52 onsets per movement, (session 12) 50 onsets per movement, which we considered sufficient to perform our analysis. The algorithm applied to perform onset detection was based on a thresholding technique that evaluated the spatial as well as temporal characteristics of the EMG data to perform a decision (see [8] for more details). For each given movement, after an onset was detected, a segment of 200ms was collected from

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**Abstract**

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each muscle channel and successively stored in an "onset" matrix (4 columns, 1 per muscle channel).

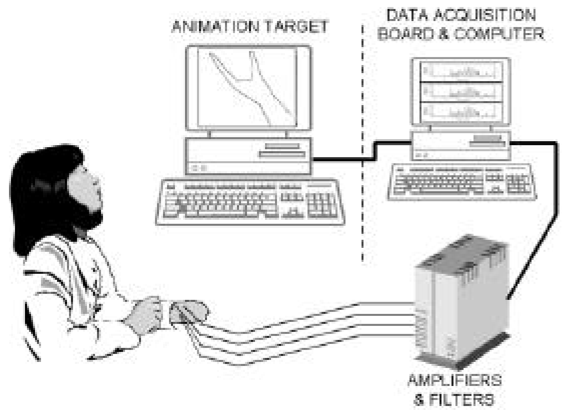


Fig.1 Experimental setup

*B. Time series analysis using Davies-Bouldin cluster validation technique*

*(1) Individual analysis:* Initially, we performed an individual analysis on the data obtained from each experimental day. For a given wrist movement, and following each onset detection, we calculated the time series coefficients for each of the muscles. These were the columns in an "onset" matrix. We generated the feature spaces separately for the AR, MA, and ARMA models. For each model type we repeated the feature extraction while uniformly increasing the order and number of coefficients. The Davies Bouldin indices (DBIs) were calculated for each of the resulting feature spaces, as follows:

$$DBI \equiv \frac{1}{N}\sum_{I=1}^{N} R_i \tag{1}$$

$$\mathrm{R}_{ij} \equiv \frac{S_i + S_J}{M_{ij}} \tag{2}$$

$$Si = \left\{ \frac{1}{T_i} \sum_{j=1}^{Ti} \left\| x_j - A_i \right\|_2^{\,q} \right\}^{\frac{1}{q}} \tag{3}$$

$$M_{ij} = \left\{ \sum_{K=1}^{N} \left| a_{ki} - a_{kj} \right|^{p} \right\}^{\frac{1}{p}} \tag{4}$$

where $R_{ij}$ is the cluster to cluster similarity, $S_i$ the dispersion of the $i^{th}$ cluster, $M_{ij}$ is the Minkowski distance between the centroids of clusters $i^{th}$ and $j^{th}$ and $R_i=\max(R_{ij})$ $i \neq j$. In our analysis we utilized q=2 and p=2. Thus, $S_i$ became the Euclidean distance between the points of a cluster to the centroid of the cluster and $M_{ij}$ the Euclidean distance between centroids.

For each given model and each experimental day, the resulting DBIs were stored on matrices sized 10x10 (rows= increasing order of model; columns=increasing number of coefficients). The limit of order 10 for each model type was chosen to maintain the evaluation within the working limits of modern DSP processors. In addition, the use of up to 10 coefficients allowed us to evaluate trends in the results. In the case of the ARMA model, the total number of coefficients was 20 in order to allow a uniform contribution of both types of coefficients and to obtain results that could be compared with those obtained with the AR and MA models.

*(2) Combined analysis:* In order to determine which configuration behaved in an optimal way during the three experimental days, we pooled all the onsets utilized during the individual analysis in a single set. Subsequently, we proceeded to evaluate the feature spaces for each given model and a uniformly increasing model order and number of coefficients. Again, the resulting DBIs were stored in 10x10 matrices.

We were able to obtain only minimal improvements on class separability following significant increases on the order of model and number of coefficients. Because larger orders and number of coefficients are computationally more expensive, we used a tolerance value to determine which was the optimal configuration from a computational as well as a class separation viewpoint. This tolerance value was calculated from each DBI matrix as the increase of 5% over the minimum DBI index (i.e., tolerance value = 1.05 x (minimum DBI)). We chose the value of 5% because we felt that an increase in 5% over the minimum DBI will not greatly degrade class separability, but it will significantly improve the performance of the resulting system. Thus, for each given DBI matrix, once the minimum DBI value was found, we used the tolerance to find the configuration with the smallest order and number of coefficients that had a DBI below the tolerance value.

## III. RESULTS

### *A. Individual analysis*

The smallest DBIs were continuously obtained with AR models (Table I). In this case, the indices ranged from 1.155 to 3.304. In the case of MA and ARMA, the indexes ranged from 6.631 to 23.678, and from 7.206 to 23.951, respectively. From these values we can observe that the DBIs obtained by the feature spaces based on AR model didn't overlap with those obtained by MA and ARMA models.

A more detailed study of the indices revealed that above a certain order and number of coefficients, the feature spaces with a larger number of coefficients also presented larger

DBI values (Fig. 2). This behavior was observed for orders larger than 4 and number of coefficients larger than 1. In addition, we noted that for increasing orders of the model, the DBI indices attained larger values (Fig. 3). This behavior presented small fluctuations, but it become more and more evident as a larger number of coefficients was utilized. This behavior was observed, depending on the experimental day, for orders larger than 3, 4, or 5, and number of coefficients larger than or equal to 1 and larger than 2.

Finally, when we applied the tolerance criteria to the AR model, we obtained the optimal configuration as follows:

day 10: order 4 and 2 coefficients (DBI=1.210).
day 11: order 4 and 2 coefficients (DBI=1.785).
day 12: order 4 and 2 coefficients (DBI=1.512).

TABLE I
Wrist movements: means and standard deviations of the DBI values obtained in each experimental day for each of the models: AR, MA; ARMA.

| | | day10 | day11 | day12 |
|---|---|---|---|---|
| AR | mean | **1.322** | **1.951** | **1.68** |
| | std | 0.21 | 0.225 | 0.277 |
| MA | mean | **10.544** | **11.678** | **12.21** |
| | std | 2.65 | 2.735 | 3.063 |
| ARMA | mean | **10.19** | **11.343** | **10.507** |
| | std | 2.348 | 2.606 | 1.995 |

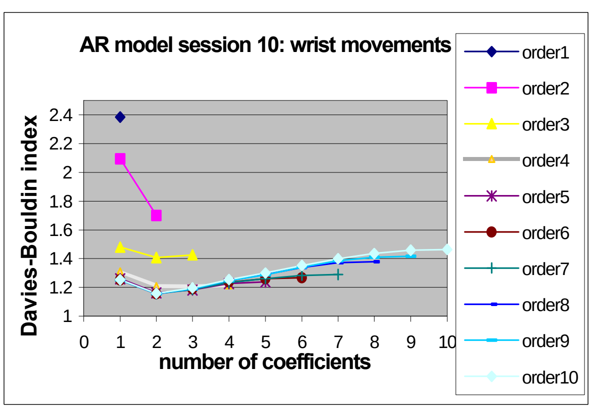


Fig.2 Experimental day 10: Dependence of the DBIs with the number of coefficients.

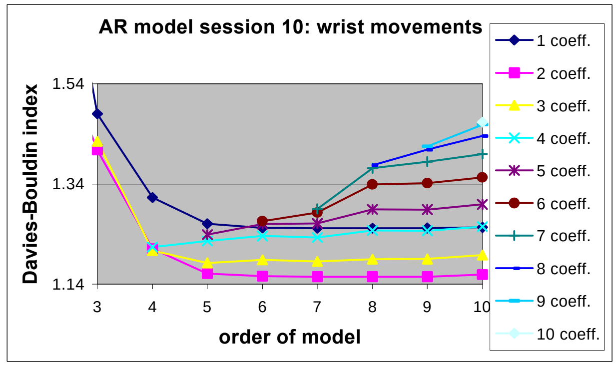


Fig.3 Experimental day 10: Dependence of the DBIs with the order of model. Note, the configurations with DBI slightly smaller that the one presented by the optimal configuration (order 2, 4 coefficients).

## *B. Combined analysis*

Once again the feature spaces based on the AR model produced the smallest DBI values (Table II). This time the values ranged from 1.6297 to 3.399. Note, that the spread of the data and the mean and standard deviations don't differ to a large extend from the results obtained during the individual analysis. The range of values derived from the MA and ARMA models was from 13.844 to 31.797 and 14.283 to 31.139, respectively.

TABLE II
Wrist movements: means and standard deviations of the DBI values obtained from the pooled coefficients obtained during all the experimental days. Results obtained for AR, MA, and ARMA models.

| | | AR | MA | ARMA |
|---|---|---|---|---|
| **wrist** | mean | **1.851** | **18.081** | **17.979** |
| | std | 0.343 | 4.325 | 3.901 |

We noted once more that the DBIs obtained from the feature spaces based on the AR model didn't overlap with those derived from the MA or ARMA models. Subsequently, we applied the tolerance criteria to the AR model and found that the optimal DBM value was order 4 and 2 coefficients (DBM=1.662). Note that this configuration is the same for all the experimental days during the individual analyses.

Furthermore, we observed the same relationship between the number of coefficients and the DBIs that was already observed during the individual analysis. In this case, the relationship appeared for orders larger than 4 and number of coefficients larger than 1. We also noticed that when the order of the model increased, the DBIs increased as well. This behavior was observed for orders larger than 3 and a number of coefficients larger than 2.

## IV. DISCUSSION

The use of an AR model has been favored by the results from both individual and combined analyses. Additionally, the results (model type, order, and number of coefficients) were consistent with those obtained by other investigators using surface EMG data and more standard methods of time-series identification [1, 2]. The reasons for this likeness between the results obtained with surface EMG recordings and intramuscular EMG might be due to the low recruitment level produced at the onset of the muscle contraction. Because the units with lower conduction velocity (lower frequency components) are recruited first, the spectra of intramuscular recordings at the onset of the contraction might be similar to the spectra of surface EMG recordings during sustained contraction.

We also noted that the model type, order, and number of coefficients that provided an optimal class separation was the same for the individual and combined analysis: order 4 and 2 coefficients. Additionally, in both cases (individual and combined analysis) the spread of the DBI indices and the mean and standard deviation values were comparable. These facts indicate that the distribution of samples in the different feature spaces was rather consistent across different days. This result is important when we consider the use of this feature space in a pattern recognition system since, in this case, it would be possible to obtain a consistent performance of the system across different days.

## V. Conclusion

The Davies-Bouldin cluster validation technique has permitted us to determine the optimal configuration (model type, order, and number of coefficients) from a pattern recognition standpoint. We have obtained results comparable to those from surface EMG studies although we recorded intramuscularly, and the type of movements and muscles were different from previous studies. The analysis of DBIs from the different feature spaces generated important information about the separability and consistency of the data across different experimental days. Also, the DBI values permitted us to evaluate the comparative separability of AR versus the MA, and ARMA models. Best results overall were obtained with an AR model of order 4 and 2 coefficients.

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