Use of Regularized Discriminant Analysis Improves Myoelectric Hand Movement Classification

Citation for published version:

Digital Object Identifier (DOI):
10.1109/NER.2017.8008373

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
2017 8th International IEEE/EMBS Conference on Neural Engineering (NER)

General rights
Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.
Use of Regularized Discriminant Analysis Improves Myoelectric Hand Movement Classification

Agamemnon Krasoulis, Student Member, IEEE, Kianoush Nazarpour, Senior Member, IEEE and Sethu Vijayakumar

Abstract—Linear discriminant analysis (LDA) is the most commonly used classification method for movement intention decoding from myoelectric signals. In this work, we review the performance of various discriminant analysis variants on the task of hand motion classification. We demonstrate that optimal classification performance is achieved with regularized discriminant analysis (RDA), a method which generalizes various class-conditional Gaussian classifiers, including LDA, quadratic discriminant analysis (QDA), and Gaussian naive Bayes (GNB). The RDA method offers a continuum between these models via tuning two hyper-parameters which control the amount of regularization applied to the estimated covariance matrices. In this study, we performed a systematic classification performance comparison on four datasets. Hand motion was decoded from myoelectric and inertial data recorded from 60 able-bodied and 12 amputee subjects whilst they performed a range of 40 movements. We found that when the regularization parameters of the RDA classifier were carefully tuned via cross-validation, classification accuracy was statistically higher by a large margin as compared to any other discriminant analysis method (average improvement of 13.7% over LDA). Importantly, our findings were consistent across the able-bodied and amputee populations. This observation provides supporting evidence that our proposed methodology could improve the performance of pattern recognition-based myoelectric prostheses.

I. INTRODUCTION

Pattern recognition-based myoelectric control aims at deciphering movement intention from biosignals to achieve naturalistic control of external devices, such as prosthetic hands and exoskeletons. In the myoelectric control literature, linear discriminant analysis (LDA) is the most extensively used method for motion classification for a number of reasons, including ease of implementation, computational efficiency, and performance robustness [1]–[3]. In this work, we review the efficacy of a general family of discriminant analysis and class-conditional Gaussian models in the context of hand motion classification.

II. BACKGROUND

Discriminant analysis is a family of supervised probabilistic models which assumes class-conditional multivariate Gaussian densities [4]. LDA is a special case of this family where a common covariance matrix, often referred to as the pooled covariance or within-class scatter matrix, is shared among classes. This assumption leads to linear decision boundaries (i.e. hyperplanes). In LDA, a test data point \( x \) is assigned to the class \( c \) for which the linear discriminant function \( \delta_c(x) \) is maximized:

\[
\delta_c(x) = x^\top \Sigma^{-1} \mu_c - \frac{1}{2} \mu_c^\top \Sigma^{-1} \mu_c + \log \pi_c, \tag{1}
\]

where \( \pi_c \) and \( \mu_c \), for \( c = 1, \ldots, C \), are the prior probabilities and class means, respectively, \( \Sigma \) is the pooled covariance matrix, and \( C \) is the number of classes. The prior probabilities, mean vectors, and pooled covariance matrix can be estimated from the training data:

\[
\hat{\pi}_c = \frac{N_c}{N} \tag{2}
\]

\[
\hat{\mu}_c = \frac{1}{N_c} \sum_{n \in c} x_n \tag{3}
\]

\[
\hat{\Sigma} = \sum_{c=1}^{C} \sum_{n \in c} \frac{1}{N - C} (x_n - \hat{\mu}_c) (x_n - \hat{\mu}_c)^\top, \tag{4}
\]

where \( N_c \) is the number of training instances in class \( c \), and \( N \) is the total number of training samples. The posterior probability for class \( c \) is given by the softmax function:

\[
p(y = c|x) = \frac{e^{\delta_c(x)}}{\sum_{c=1}^{C} e^{\delta_c(x)}}. \tag{5}
\]

Quadratic discriminant analysis (QDA) is another type of class-conditional Gaussian model which does not make the LDA assumption (i.e. shared covariance matrix), thereby a separate covariance matrix has to be estimated for each class. In this case, the decision boundaries are quadratic in feature space and the discriminant functions are given by:
Regularized discriminant analysis (RDA) is a method that generalizes LDA and QDA and provides a continuum of models between the two [5]. Similar to the QDA classifier, the class covariance matrices for this model are separate, however they are regularized toward the pooled covariance matrix. A schematic representation of this family of models is shown in Fig. 1. It is worth noting, that the GNB model is occasionally referred to as diagonal quadratic discriminant analysis (DQDA).

\[
\delta_c (x_s) = -\frac{1}{2} x_s^\top \Sigma_c^{-1} x_s + \hat{\mu}_c^\top \hat{\Sigma}^{-1} x_s
\]
\[
- \frac{1}{2} \log |\Sigma_c| + \log \pi_c - \frac{1}{2} \hat{\mu}_c^\top \hat{\Sigma}^{-1} \hat{\mu}_c,
\]

where \( \Sigma_c \) is the covariance matrix of class \( c \), which can be estimated from the training data:

\[
\hat{\Sigma}_c = \frac{1}{N-1} \sum_{n \in c} (x_n - \hat{\mu}_c)^2
\]

Regularized discriminant analysis (RDA) is a method that generalizes LDA and QDA and provides a continuum of models between the two [5]. Similar to the QDA classifier, the class covariance matrices for this model are separate, however they are regularized toward the pooled covariance matrix and take the form:

\[
\hat{\Sigma}_c (\alpha) = \alpha \hat{\Sigma} + (1-\alpha) \hat{\Sigma}_c,
\]

where \( \alpha \) controls the amount of regularization. For \( \alpha = 0 \), we recover LDA, and for \( \alpha = 1 \), we recover QDA. A different form of regularization occurs when the estimated covariance matrices are regularized toward diagonal matrices:

\[
\hat{\Sigma} (\gamma) = (1-\gamma) \hat{\Sigma} + \gamma \text{diag}(\hat{\Sigma})
\]

The two regularization approaches are orthogonal, and can be thus combined into:

\[
\hat{\Sigma}_c (\alpha, \gamma) = \alpha (1-\gamma) \hat{\Sigma} + (1-\alpha) (1-\gamma) \hat{\Sigma} + \left( \alpha \gamma \text{diag}(\hat{\Sigma}_c) + (1-\alpha) \text{diag}(\hat{\Sigma}) \right).
\]

The model described by Eq. (11) leads to a general family of models which treats as special cases various well-known classifiers including LDA, QDA, Gaussian naive Bayes (GNB), and diagonal linear discriminant analysis (DLDA), that is, an LDA model with diagonal pooled covariance matrix. A schematic representation of this family of models is shown in Fig. 1. It is worth noting, that the GNB model is occasionally referred to as diagonal quadratic discriminant analysis (DQDA).

### III. METHODS

#### A. Datasets

In this study, we used four datasets to evaluate and compare the performance of the family of classifiers introduced in the previous section. The first two datasets are publicly available, as part of the Ninapro project\(^1\) (databases 2 and 3 in Atzori et al. [3]). The latter two datasets were collected by the authors using the Ninapro protocol and made available on the same repository. One difference between the two pairs of datasets is that, for the first pair, the standard Delsys\(^\text{TM}\) Trigno\(^\text{TM}\) sensors\(^2\) were used which incorporate surface electromyogram (sEMG) electrodes and accelerometers. For the latter two datasets, the Delsys\(^\text{TM}\) Trigno\(^\text{TM}\) IM system was used which also includes gyroscopes and magnetometers. The inertial measurement data (acceleration, angular velocity, magnetic field) were used in their raw format along with sEMG measurements to decode hand motion intention [6]. General information about all four datasets, including number of participants, medical conditions and input sensing modalities are presented in Table I.

In all experiments, eight sensors were equally placed around the subjects’ forearm, and four sensors targeted the extensor digitorum communis, flexor digitorum superficialis, biceps, and triceps brachii muscles (Fig. 2). The participants sat in a chair and performed six repetitions of 40 movements which were instructed to them on a computer screen. The exercises included individuated finger, wrist, grasp and functional movements [3]. Myoelectric and inertial data were

\(^1\)http://ninapro.hevs.ch
\(^2\)http://www.delsys.com/
recorded at sampling frequencies of 2 KHz and 128 Hz, respectively.

B. Signal pre-processing and feature extraction

Myoelectric signals were digitally band-pass filtered in the range 20 Hz to 500 Hz. By using a shifting window approach, four time-domain sEMG features were extracted from each channel, namely the mean absolute value (MAV), waveform length (WL), 4th-order auto-regressive (AR) and log-variance (Log-Var) [7]. The length of the window was set to 256 ms and the increment to 50 ms. For accelerometry (ACC) and inertial measurements (IMs), the mean value (MV) within the processing window was calculated. Thus, a total number of 10 features was extracted from each sensor for datasets 1 and 2 (7 sEMG, 3 ACC features), whereas the same figure for datasets 3 and 4 was 16 (7 sEMG, 9 IM features). Hence, the input feature space was 120- and 192-dimensional for the two pairs of datasets, respectively.

C. Cross-validation (CV) and hyper-parameter tuning

For each subject and movement, data from five repetitions were used to train models and the left-out repetition data were used to assess model performance. This procedure was repeated six times, hence resulting in 6-fold cross-validation (CV). To tune the regularization hyper-parameters \(\alpha\) and \(\gamma\) for RDA, a grid search was performed in the range \([0, 1]\) with a step size of 0.05. In this case, inner-fold CV was used and the parameter values which yielded the highest average performance were selected.

D. Performance assessment

The class distribution of the test folds was balanced by removing a large proportion of the instances corresponding to the rest class. Decoding performance was then evaluated by using the standard classification accuracy (CA) metric.

IV. RESULTS

A performance comparison of five discriminant analysis classifiers (LDA, QDA, GNB, DLDA, RDA) is shown in Fig. 3. For all four datasets, RDA consistently outperformed all other classifiers and it was followed by LDA, GNB, QDA and DLDA. The average CA median difference between RDA and LDA was 13.7%. All performance differences between classifiers were statistically significant \((p < 10^{-3},\) Friedman Test followed by pair-wise Wilcoxon rank-sum tests with Šidák correction for multiple comparisons). Representative confusion matrices for one amputee subject (dataset 4) are shown in Fig. 4 for LDA and RDA.

The distribution of hyper-parameters \(\alpha\) and \(\gamma\) for RDA as selected by CV is shown in Fig. 5. The optimal selection for \(\gamma\) was almost consistently 0 (with very few exceptions where it was 0.05), whereas for \(\alpha\) it was in the range 0.15 to 1.

V. DISCUSSION

A. Comparison of models, overfitting and regularization

The RDA classifier consistently outperformed all other models. This was expected, since the RDA model is flexible and can treat all other models as special cases (Eq. 11, Fig. 1). The two hyper-parameters of the RDA classifier were tuned such that the cross-validated CA was maximized, therefore, it was guaranteed that its performance would be at least as good as that of any other model.

The LDA model assumption, that is, classes share a common covariance matrix, is very strong and fundamentally wrong. One would expect that QDA should outperform LDA since it is more flexible and does not make this assumption. The reason why this is not often the case is that QDA is
that reason, it should not be surprising that the optimal value for \(\alpha\) was almost consistently 0 (Fig. 5).

B. Computational and memory requirement considerations

One strong advantage of the LDA model is that decision boundaries are linear in feature space. Consequently, the time complexity of assigning class probabilities to a test sample is \(O(CD)\), that is, it scales linearly with the feature dimensionality. The space complexity for LDA is also \(O(CD)\). For general class-conditional Gaussian models like QDA and RDA that are implemented efficiently, that is, when inverse covariance matrices are precomputed and stored in memory, the computational complexity is \(O(CD^2)\) and space complexity is \(O(CD^3)\). For small to medium-sized feature spaces, this would not pose a problem for real-time implementations.

VI. CONCLUSIONS

In this study, we reviewed and performed a systematic comparison of discriminant analysis models on hand motion classification. We demonstrated that a large improvement in CA can be achieved, both for able-bodied and amputee subjects, by using the RDA algorithm, as compared to the commonly used LDA model. The regularizing parameters of the RDA model can be easily tuned via hold-out or cross-validation.

Our study suggests that pattern recognition-based myoelectric control systems have the potential to benefit from deploying the RDA method in the decoding stage. Further verification of our results during real-time control paradigms is required and currently seen as a future research direction.

REFERENCES


