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Person-Specific Gesture Set Selection for Optimised Movement Classification from EMG Signals

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***Abstract*— Movement classification from electromyography (EMG) signals is a promising vector for improvement of human computer interaction and prosthetic control. Conventional work in this area typically makes use of expert knowledge to select a set of movements *a priori* and then design classifiers based around these movements. The disadvantage of this approach is that different individuals might have different sets of movements that would lead to high classification accuracy. The novel approach we take here is to instead use a data-driven diagnostic test to select a set of person-specific movements. This new approach leads to an optimised set of movements for a specific person with regards to classification performance.**

I. Introduction

Movement classification from surface Electromyography (EMG) signals to control prosthetics and other human computer interface devices is an important and challenging problem. The conventional approach to EMG based movement classification is to select some number of movements, experimentally acquire the EMG data per movement per subject, and then design classifiers to distinguish between those movements either in general or on a per subject basis. This conventional approach neglects the fact that the most separable movements (and hence the optimum selection to maximise classifier performance) vary between individuals.

The novel aim of this paper is to investigate how to optimally select a set of movements from EMG data for a specific individual, which to our knowledge has not yet received attention in the literature. This work has applications in personalised prosthetic control and more generically control in human computer interfaces.

Early research into EMG-based movement classification [1]–[4] and recent commercial surface EMG devices such as the Myo Armband [5] addressed the problem of classification from a small pool of movements only. Recently, there has been a trend towards developing EMG movement classification for larger gesture sets [6]. None of these approaches, however, have directly addressed the issue of selecting person-specific movements that would optimise classification performance.

In this work, for the first time, we change perspective on the EMG movement classification problem, and directly focus on selecting a set of person-specific gestures from a superset. We use a data-driven approach as opposed to *a priori* selection of movements from expert deduction on the general separability of movements. This has the key advantage that the movement set selection can easily be automated and made person-specific for each distinct task or application, via a rapid diagnostic test. This paves the way for a new approach to the EMG control of devices that is tailored to both individuals and tasks.

An additional benefit of our approach is that it enables improvements in classification performance at a relatively small additional cost to time in the experimental steps. This is because experiment design, set up and the (ethical) approval process is the major hurdle to gathering EMG data for classification, against which the diagnostic test proposed here is relatively inexpensive. In a practical scenario, the diagnostic testing may be done by gathering data on more movements than is required for the intended application and then sub-selecting from those movements for optimum classification.

The experimental data used here to evaluate gesture selection methods was surface EMG recorded as part of the Non-Invasive Adaptive Prosthetics (*NINAPRO*) project [7], [8]. NINAPRO provides an open source database of EMG data on 53 movements (including *rest*) across 27 subjects. Here, the *rest* movement was treated as a base since in practical applications it is often necessary or useful to distinguish when an individual is not attempting a movement.

In order to select person-specific gesture sets, we propose and evaluate three different gesture set selection algorithms. We compare performance to a baseline of arbitrarily selecting the movements in the order they are presented by Atzori *et al* [6]. The three metrics are: 1. maximising the minimum distance between means of each movement in Euclidean space; 2. maximising the minimum KL-divergence; and 3. training the classifier on the full 53 movements first, then taking the movements in order of highest classification accuracy.

The Mean Absolute Value (MAV) was selected as the feature representation due to its simplicity, high performance in classification tasks [9] and lack of hyper-parameters. Five standard classifiers types were evaluated to ensure results were not an artifact of the particular assumptions of a specific classifier. The five types of classifier are K Nearest Neighbours (KNN), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) with Radial Basis Function Kernels (SVM-RBF) and with Linear kernels (SVM-L) and Decision Trees (DT).

In order to aid researchers all code used and raw results obtained will be made available via https://github.com/Lif3line under a modified MIT Licence.

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II. Preprocessing and classification

The *NINAPRO* database 1 (see [7] for full details) was used in this investigation, which covers 27 subjects performing 10 repetitions of 52 movements with a *rest* movement between each (for a total of 53 movements). The signals used here were the 10 channel surface EMG data and a-posteriori refined movement labels. EMG signals are stated to be root mean squared rectified and sampled at 100Hz with a bandwidth of 0-25Hz.

A. EMG signal preprocessing

Preprocessing steps:

1) Each EMG channel was passed through a 5Hz, second-order, zero phase, low-pass Butterworth filter
2) Signals were split into a continuous stream of windows
   - Window length: 400ms (40 samples)
   - Window Increment: 10ms (1 sample)
3) Each window was labelled as belonging to the movement with the most number of points in the window: always a case of *rest* vs some other movement
   - For $50/50$ splits *rest* was assumed
4) Movements were decoupled by removing windows that straddle a boundary: one window lengths worth of windows removed before and after a *non-rest* movement
5) The MAV was extracted from each channel of each window

B. Feature selection and classification algorithms

There are 10 repetitions of each movement per subject in the database; repetitions $\{1, 3, 5, 7, 9\}$ were used for training and $\{2, 4, 6, 8, 10\}$ were used for testing. This split is chosen over n-fold validation to be consistent with previous work and because adjacent windows share information meaning random selection would cause the training and testing sets to be non-independent. Inputs were standardised for KNN, SVM-RBF and SVM-L classified by weighted column mean and standard deviation.

The Mean Absolute Value (MAV) was selected as the feature representation due to its simplicity and high performance in classification tasks [9]. The Mean Absolute Value is defined as the mean of all values per channel per window. This leads to a 10 dimensional feature space,

$$MAV\ (channel) = \frac{1}{T}\sum_{t=1}^{T}|x_t| \tag{1}$$

$T : Window\ Length\ (signal\ duration)$

Due to the large amount of data on the *rest* movement compared to other movements both the training and testing sets are biased. To avoid wasting data in the testing set performance was measured as the average of the per class percentage corrected classified points; this is known as the average accuracy in machine learning literature.

$$Average\ Accuracy = \frac{1}{M}\sum_{m=1}^{M}\frac{correct\_predictions_m}{N_m} \tag{2}$$

$m : Movement$
$M : Number\ of\ movements$
$N : Number\ of\ test\ points$

Each classifier was trained on training sets that only contained the X movements selected by the selection algorithms to produce the results described. Due to the large amount of *rest* data in the training set the *rest* was randomly downsampled so that there were only as many examples of *rest* as the next most represented movement.

Classifier details:

- K Nearest Neighbours (KNN)
  - 10 Euclidian Neighbours
- Linear Discriminant Analysis(LDA)
  - Pseudo-linear fit
- Support Vector Machine with Radial Basis Function Kernel (SVM-RBF)
  - Multiclass method: One vs All
  - Sequential Minimal Optimisation
  - Box Constraint of 1
  - MATLAB inbuilt heuristic kernel scaling
- Support Vector Machine with Linear Kernel (SVM-L)
  - Multiclass method: One vs One
  - Sequential Minimal Optimisation
  - MATLAB inbuilt heuristic kernel scaling
- Decision Tree (DT)
  - Maximum number of decision splits: 150
  - Gini's Diversity Index used as split criterion
  - Prior probabilities based on class frequencies

III. Person-specific gesture set selection

The *rest* movement is used as a base for all selection algorithms in this paper due to its utility in many real world applications. The baseline selection method is to start with *rest* then add movements in the order they are presented by Atzori *et al* [6]; as the movements are presented in groups of similar actions, a priori, this set could reasonably be assumed to be sub-optimal.

Due to the high dimensionality of the problem (up to 53 movements, 10 dimensional feature space) exhaustive classifier training of possible movement combinations is computationally inhibitive similarly exhaust searches of movement combinations even for simple distance metrics is computationally infeasible. The three selection algorithms evaluated here, therefore, all build up a set of movements for an individual one movement at a time by maximising a separability criteria:

A. Maximisation of minimum distance between movement means

The mean of the feature representation of an individual's different movements is taken. The selection algorithm computes the Pythagorean distances from each not currently selected movement mean to all selected movement means, the minimum distance to any movement in the currently selected set is then saved and the the movement that has the largest minimum distance is the next candidate for selection.

$$Best\ m = max(min(|\mu_m - \mu_{g)}|)), m \not\supseteq g \tag{3}$$

$m : Movement$
$\mu : Movement\ mean$
$g : Currently\ used\ set\ of\ movements$

B. Maximisation of minimum symmetric Kullback-Leibler Divergence between movements

Similarly the Kullback-Leibler divergence (KL) is computed between all movements not currently select and the selected movements. The closest divergence for each not selected movement compared to all the selected movements is retained for each not selected movement and the not selected movement with the largest minimum divergence is the next candidate for selection.

$$Best\ m = max(min(D_{KL}(m||g) + D_{KL}(g||m))), m \not\supseteq g \tag{4}$$

$D_{KL} : Kullback\text{-}Leibler\ divergence$

C. Selection of superset highest performance movements

This algorithm differs in that it is both individual and classifier specific. Each classifier was trained on the full 53 class problem for each subject, the base class is still *rest* however all other movements are selected in descending order of performance by the classifier on the 53 class problem. The single class with the highest classification rate was selected first then the movement with the second highest classification rate and so on.

$$Best\ m = max(performance(m)), m \not\supseteq g \tag{5}$$

IV. Results

For all gesture selection methods proposed above our baseline performance comparison was chosen as the order of gestures given by Atzori *et al* [7], which is their experimental order that groups together similar movement types such as grasping. This order is chosen to represent how a naive selection method might act as an appropriate number of random selections was too computationally expensive to compute.

The first main result was that all proposed selection methods generally gave higher classification accuracy than the baseline method except in the case of the LDA classifier (Figure 1). The baseline choice of movement subsets generally performed at up to $\sim 10\%$ worse than the superset performance selection algorithm for up to about 30 gestures.

We found that the best gesture selection method of the three proposed, across all five classifiers, was the superset performance selection algorithm. This is presumably due to the fact that the algorithm not only tailors movement selection to an individual but also to the classifier in use, thus optimising not just for differences in individuals but also for

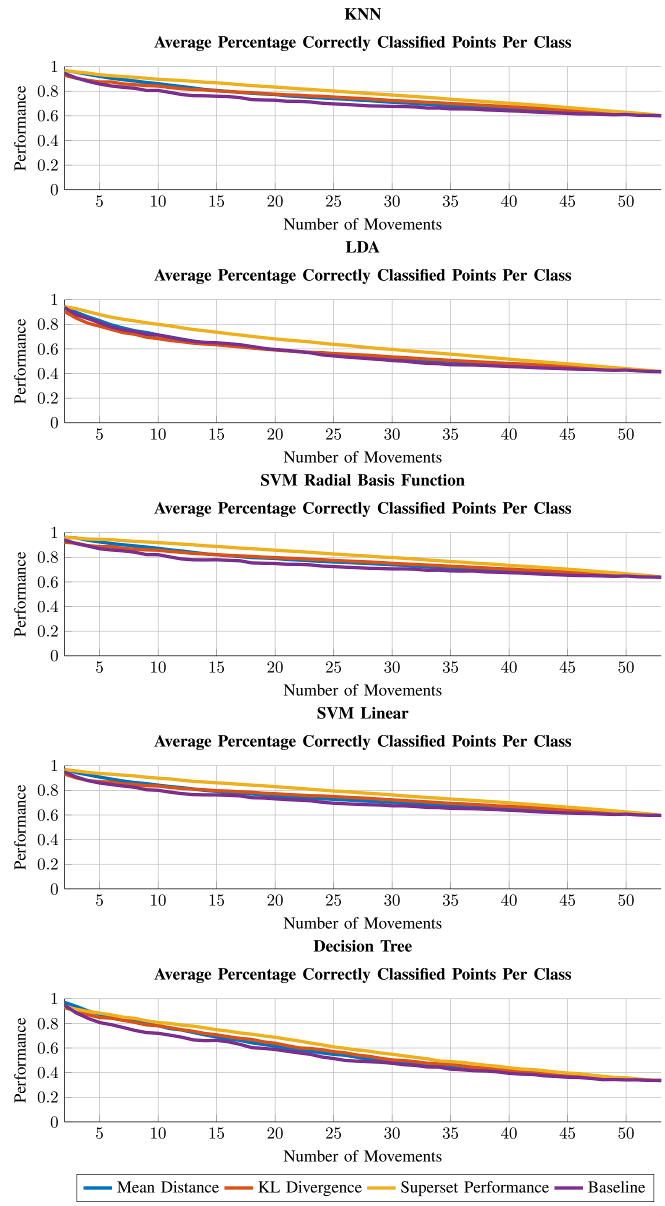

Fig. 1. Classifier performance relative to the number of movements under consideration for the four different movement choice methods averaged across all 27 subjects. The superset performance algorithm leads and the baseline selection (random selection), trails near unanimously.

how those differences interact with the inherent assumptions made by each classifier.

The other two selection algorithms, mean distance and KL divergence, performed similarly to each other and generally above the baseline but below the superset performance. Their similarity is likely due to the metrics both utilising the difference between means.

As would be expected, the difference between selection algorithms makes the most difference for smaller subsets because as more movements are included the diversity between subsets is reduced. Similarly the performance drop for adding more movements is generally slightly increased when the subset is small. Otherwise the relationship is fairly constant when using superset performance based selection, leading to

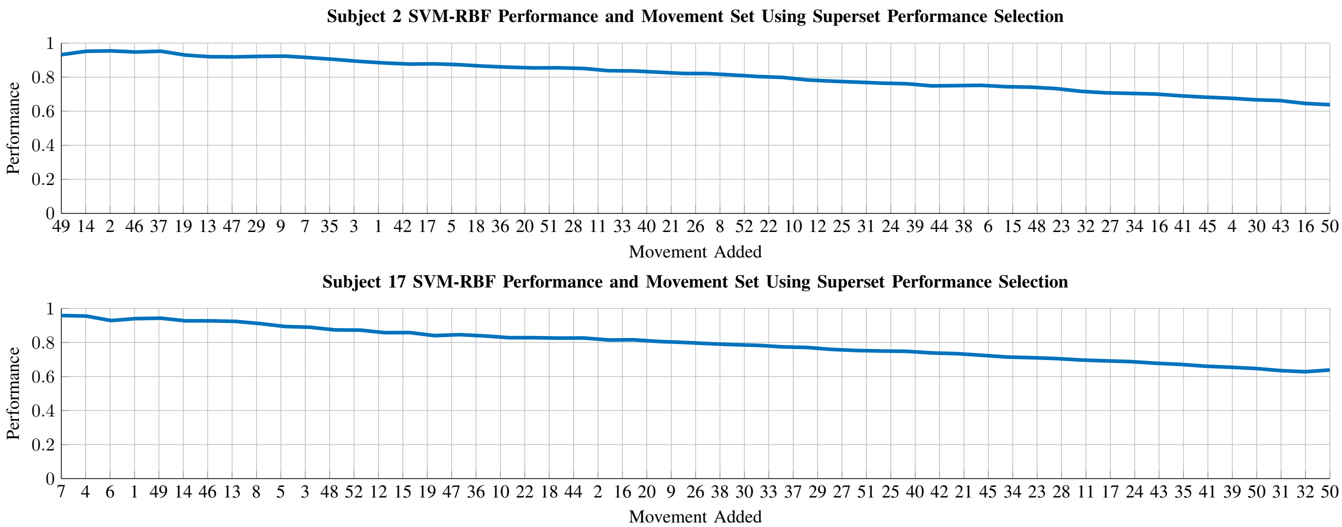

Fig. 2. Performance for two randomly selected subjects as more movements are added to the set being classified. Most importantly the performance remains similar between the individuals but the set of movements is vastly different in order to achieve the same level of performance.

a near linear relationship between number of movements and performance especially so for the SVM-RBF.

The SVM-RBF was the best classifier tested, with performance (using the superset performance based selection) dropping fairly linearly from 96% to 64%, equating to a drop of $\sim 0.6\%$ per additional movement. This result is very promising and paves the way for optimisation based on classifier performance versus number of recognised movements, as well as providing a baseline expectation of classifier performance for a given number of movements.

Finally, we chose the best performing diagnostic test, superset performance selection algorithm with SVM-RBF classification, and evaluated it on two different subjects. We found that the classification accuracy was similar across subjects, but that crucially, the gestures selected were completely different across subjects (Figure 2). This justifies the need for a person-specific classification method and emphasises the advantage of the proposed approach.

V. Conclusion

We have demonstrated that the best algorithm for selecting a subset of movements from a larger set is the superset performance; training a classifier on the full set then choosing movements based on descending individual performance order. We have also demonstrated that for a standard SVM-RBF classifier a relatively small average performance trade off of $\sim 0.6\%$ per additional movement is observed.

This work paves the way for rapid deployment of individual specific movement classification for use in prosthetic control and more generally for human computer interaction. It allows for experiments to be designed around gathering movements without having to determine optimal movements ahead of time as more movements may be gathered than required and the optimal movements selected for classification performance at a relatively small overhead. This new perspective also allows for trade off between number of movements and classifier performance allowing for specific applications to be optimised along these lines as well as optimised for the individual.

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