SUBSET SELECTION OF MYOELECTRIC CHANNELS

A Genetic Algorithm for Subset Selection of Myoelectric Channels for Patients following TMR Surgery

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Abstract: State of the art self powered prostheses make use of the surface myoelectric signal for motor control. With increasing height of the amputation, control by residual muscles becomes less intuitive and physiologic. Targeted muscle reinnervation (TMR), a surgery technique to increase the number of control sites available in combination with multichannel surface electromyography allows for improved prosthesis control. This paper presents a genetic algorithm that determines a channel subset with high classification accuracy out of a given number of channels recorded from the reinnervated area of a patient.

1 INTRODUCTION

Current generations of self powered artificial limbs for the upper extremity are controlled by electromyographic signals recorded from the surface of the skin (Scott and Parker, 1988). Despite ongoing research for more advanced neural interfaces (Navarro et al., 2005), the surface myoelectric signal (MES) is currently the preferred way for estimating muscle activity of residual muscles. Commercially available prostheses systems are typically comprised of three logical building blocks, the pickup electrodes, a controller and the mechanical arm itself. Two bipolar electrodes are placed on synergist and antagonist muscles of the residual limb where myoelectric activity is recorded, amplified and fed to the controller for further processing. The controller is responsible for translating muscle activity in joint movement. A common method is to rectify and low pass filter the myoelectric signal to get an estimation for the mean absolute value (MAV).

1.1 Control Methods

Depending on the height of the amputation, available prostheses systems may offer up to three active degrees of freedom. Control is usually achieved by having as many states as available degrees of freedom and controlling each individual degree of freedom with the same pair of electrodes at a time. State transition is achieved by applying a special signal, e. g. a simultaneous contraction of synergist and antagonist muscles. The limited information of the mean absolute value and a single pair of electrodes led to research on pattern recognition methods to make use of further information contained in the MES, as handling more degrees of freedom becomes cumbersome with the above mentioned method.

Features derived from the MES may be grouped in time-domain, frequency domain and time-frequency methods. Features calculated in the time domain are e. g. waveform length, zero crossings and slope sign changes, whereas time frequency methods may comprise the Fourier transform or wavelet transforms (Englehart et al., 1999). For each channel one or more feature is calculated to form a feature vector. Feature vectors recorded for each movement class are either directly used for training a classifier or dimensionality reduction (Chu et al., 2005) is applied to decorrelate features. Different classification algorithms have been deemed suitable for classification of myoelectric signals (Huang et al., 2005).

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1.2 Targeted Muscle Reinnervation

Classification algorithms allow for better discrimination of movements than traditional methods, but still require enough control sites. For transradial amputations, sufficient muscles in the residual limb remain to allow classification of different movements (Ajiboye and Weir, 2005). For shoulder disarticulation amputees however, no residual muscle from the arm may be used for control sites, thus leading to non-physiologic control of the prosthesis.

Kuiken et al. (Kuiken, 2006) identified this problem and developed the surgery method of targeted muscle reinnervation (TMR) to create additional myoelectric control signals. After amputation, nerves once supplying the limb remain unused. Similarly, muscles serve no function due to the missing limb, such as the m. pectoralis major which provides adduction and anteversion of an intact arm. Targeted muscle reinnervation surgically connects the nerves of the missing limb to these otherwise unused muscles in order to create additional myoelectric control sites. Muscles serve as natural amplifiers for the nerve signals and known methods of surface electromyography can be used to record control signals.

1.3 Problem Setting

Whereas nerve muscle mappings in the residual muscles are clearly known after amputation, the outcome of targeted muscle reinnervation varies from subject to subject. Zhou et. al (Zhou et al., 2005) used high density recordings of 127 monopolar electrodes to identify regions of activity. Huang et al. (Huang et al., 2008) applied an algorithm based on the sequential forward search method (Somol et al., 1999) to find a limited number of electrodes that contain most neural information.

This work proposes the application of a genetic algorithm to find a channel subset that maximizes the classification accuracy of a given number of channels. Previous work using principal component analysis (PCA) indicating that out of 24 bipolar electrode channels, a much smaller number sufficed to maintain high classification accuracy (Kvas and Velik, 2008). Bipolar electrodes were chosen, because they are more clinically relevant as this type is used for prosthesis control. The PCA based method would act as a filter method and is thus computationally cheap. This work extends the idea of subset selection to a wrapper approach using a genetic algorithm for improved classification accuracy. The genetic algorithm presented utilizes the output from the classifier trained on patient data as a fitness function to find the near-optimal subset for a given number of channels. A genetic algorithm was chosen over other heuristic search algorithms due to easy mapping of the problem domain to chromosom encoding and the possibility to limit the search to a given number of channels using “channel-constrained” genetic operators.

2 ALGORITHM

Genetic algorithms use principles of evolution to solve amongst others optimisation problems. A genetic algorithm operates on *chromosomes*, bit strings with elements being either ’0’ and ’1’. Each chromosome represents one possible solution within the search space. A *fitness function* determines how well a chromosome solves the problem at hand. Given a population of chromosomes, a fitness score is assigned to each individual chromosome and *genetic operators* are applied. Depending on preset rules, chromosomes are subjected to *crossover* and *mutation*, forming the base for a new generation of the population.

The presented algorithm is based on these building blocks for genetic algorithms. Slight adaptions are made to accommodate for the problem of channel subset selection.

Chromosome Encoding. In each chromosome, a bit ’1’ denotes an active channel, whereas ’0’ consequently denotes deactivation of this channel. As the algorithm takes the number of channels n to maximize classification accuracy as an input argument, only n bits can be ’1’ at any given time for the algorithm. This constraint requires modification of the crossover and mutation operations.

Fitness Function. The fitness function is fundamental to each genetic algorithm and needs to be specific for the given problem. In case for the channel subset selection, the fitness function is defined as

$$fitness = \frac{1}{classes} \sum_{i=1}^{classes} \frac{featvec_{correct,i}}{featvec_{total,i}} \quad (1)$$

with $featvec_{correct}$ being the number of feature vectors classified correctly out of all feature vectors $featvec_{total}$ for a given class i.

Selection. Roulette wheel selection (De Jong, 1975) was used to select parents for mating out of the entire population.

Crossover. Several approaches to crossover exist, most notably *single point* and *multi point* crossover.

For the algorithm at hand, neither of the above method was implemented, but a simpler *merge* crossover to meet the constraint of a constant number of channels. Given two chromosomes, an offspring was generated by merging both into a new chromosome. For the likely case that both parents are not exact copies of each other, the resulting offspring has more active channels than allowed by the constraint of a given channel number. Consequently, channels are deactivated at random until the constraint is met.

Mutation. Mutation is achieved by flipping a random single bit of a chromosome. Again, to meet the constraint of a fixed number of channels, a bit flipped from 1 to 0 requires another random bit to be flipped from 0 to 1 and vice versa.

Algorithm Pseudo Code

Algorithm 1: Pseudo Code.

input : Feature training set $feat_{train}$
Feature test set $feat_{test}$
Size of Subset n
Total Number of Channels tot
Crossover probability p_{co}
Mutation probability p_{mu}
Max number of iterations gen_{max}
Size of population pop_{max}

output: The subset yielding best performance

pop $\leftarrow$ InitPopulation(pop_{max});
fit $\leftarrow$ Fitness($feat_{train}$, $feat_{test}$, pop);
for $gen_{cur} \leftarrow 1$ **to** gen_{max} **do**
  parents $\leftarrow$ RouletteWheel(fit, pop);
  foreach *two* parents *par* **do**
    if Random $> p_{co}$ **then**
      offspring $\leftarrow$ Crossover(par);
  foreach offspring **do**
    if Random $> p_{mu}$ **then**
      offspring $\leftarrow$ Mutation(offspring);
  fit $\leftarrow$ Fitness($feat_{train}$, $feat_{test}$, offspring);
  Reinsertion(pop, offspring, fit);

Algorithm Run-Time. An exhaustive search to try all subsets of size n within tot channels gives a total of

$$invocations = \binom{tot}{n} \tag{2}$$

subsets. For the worst case of 12 channels out of 24, this would require 2704156 invocations of the Fitness function. For the genetic algorithm however, the maximum number of invocations is a function of pop_{max}, gen_{max} and the number of parents nr_{par}:

$$invocations_{ga} = pop_{max} + gen_{max} \times nr_{par} \tag{3}$$

This can be easily seen, as for the initial run, the fitness of every chromosome has to be determined. For all subsequent runs, for every new generation a maximum of nr_{par} offspring are created, thus requiring their fitness to be evaluated. For our problem at hand, if the mean population fitness was within 0.01 % of the maximum fitness, the algorithm would exit early due to convergence. Table 1 shows the convergence ratio for each of the datasets.

Table 1: Convergence Ratio.

Dataset	Runs	Converged	Ratio
“A”	575	522	90.8 %
“B”	575	503	87.5 %
“C”	575	518	90.1 %

3 METHODOLOGY

To test the suggested algorithm, surface myoelectric signals from a patient who has undergone targeted muscle reinnervation surgery were recorded. Surgery was performed on the shoulder disarticulation side of the patient at the Vienna General Hospital in December 2006 (Aszmann et al., 2008). This is so far the only surgery performed in Europe, with further patients in the United States (Miller et al., 2008).

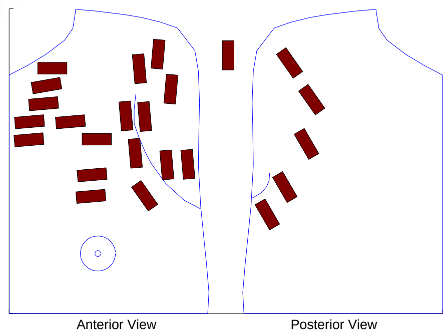

Figure 1: Two dimensional sketch of the electrode placement for 24 electrodes. The electrode floating between both views of the body was placed on the m. deltoideus.

A total of 24 active bipolar electrodes where placed on the patient following initial palpation of muscle regions and additional measurements with ultrasound to determine muscle fiber orientation. Electrodes where placed over reinnervated areas in the chest and back region as indicated by Figure 1. Signals were amplified on the electrode with a gain of 40 dB and further filtering and amplification was achieved using a custom signal conditioning board.

Signals were digitized using a National Instruments USB-6259 board at a sample frequency of 3 kHz.

Time domain features were calculated from non-overlapping blocks of 512 samples. For each channel, zero crossings, waveform length, slope sign changes and the RMS for were calculated. Features were then concatenated to form a feature vector. Classification for determining fitness was carried out using a linear discriminant analysis (LDA) classifier. As the genetic algorithm requires a high number of training and classification invocations, a linear classifier is chosen due to the lower computational requirements as opposed to multilayer perceptrons or support vector machines.

The genetic algorithm was exercised on data recorded over the last months. A session with the patient would typically involve a list of movements the patient had to perform with the phantom arm. Each movement would be demonstrated by the physiotherapist. The patient would then try to perform the same movement with the phantom arm. The patient was instructed to hold each movement at convenient contraction strength for approximately 10 seconds.

4 EXPERIMENTAL RESULTS

To test the algorithm, data recorded from a single patient available for this study was used. Each session consisted of 12 movements. No visual feedback was given to the patient while performing the movements. Table 2 shows that number of available feature vectors per session.

Table 2: Feature vectors.

Dataset	Feature Vectors	Classes
“A”	1599	12
“B”	1878	12
“C”	1686	12

The algorithm was initialized with a population size of 50 with crossover and mutation probabilities of 0.7 and 0.1, respectively. The maximum number of generations was set to 500. Subsets for 1 to 23 of the total of 24 channels were calculated. For each subset, nested 5-fold cross-validation was performed, such that classification accuracy could be indepently assessed from channel selection.

Figure 2 shows the classification accuracy for each of the subsets determined by the genetic algorithm for subset sizes of 1 to 23. Classification accuracy increases from 34.4 % for one channel to 96.57 % for 23 channels for dataset A and from 34.14 % for one channel to 92.48 % for 23 channels for dataset B. The figure further shows that classification accuracy

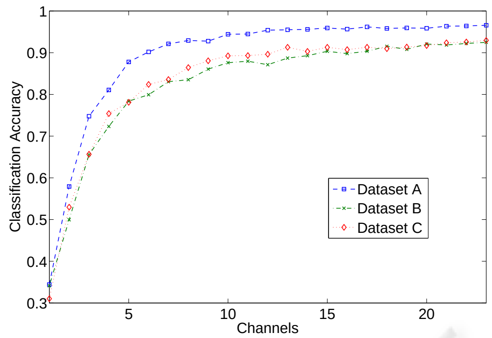

Figure 2: Maximum classification accuracy for the fittest channel subsets determined by the genetic algorithm for datasets “A”, “B” and “C”.

is quickly increasing for the first half of the channels (Dataset A: From 34.4 % to 95.39 %), but on slightly increasing for the second half of channel subsets. This shows that high classification accuracy can be maintained with a substanstially smaller set of electrodes. Table 3 gives an overview over classification accuracies for a selected number of channels.

Table 3: Classification accuracy for the specified number of channels for each dataset.

Dataset	Channels		
	1	12	23
“A”	34.43 %	95.39 %	96.57 %
“B”	34.14 %	87.12 %	92.48 %
“C”	31.03 %	89.93 %	92.94 %

Figure 3 shows the final configurations of 12 selected electrodes averaged over 5 nested cross validation loops for dataset “A”. Here, darker electrodes indicate multiple selections by each of the five subsets. White electrodes indicate no selection. When compared to the position of the nerve crafts, the electrode configuration determined by the classifier is in accordance with the expected outcome of the targeted muscle reinnervation surgery for this patient. Electrodes are selected in areas of high neural activity. Posterior, electrodes are selected in areas with reinnervation by n. radialis and both non reinnervated parts of the shoulder, accounting for muscle activity for certain shoulder-complex related muscle movements.

5 CONCLUSIONS

A genetic algorithm was used to find an near-optimal subset of electrodes out of a larger number of channels. The results show that the number of electrodes can be successfully reduced given the current setup

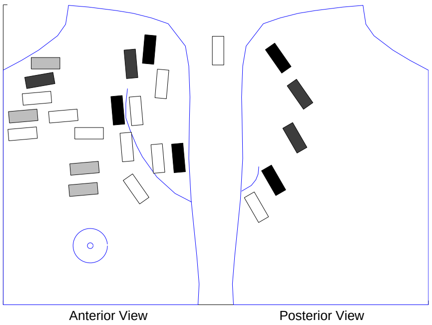

Figure 3: Channels selected by the algorithm for 12 electrodes. Results have been averaged over five cross-validation loops for the specified amount of channels. Not all loop iterations have selected the same electrodes, but a strong bias towards certain prefered channels can be observed (Darker Electrodes).

of channels. The channels that are selected also map very well to the areas where reinnervation was expected after surgery for this particular patient. However, more data from both this patient and additional patients is needed to further confirm the results. Future work will also be directed towards evaluating these results using online realtime data.

This result is primarily important as an indication for prosthesis fitting were a smaller number of surface electrodes allows for easier fitting and far simpler socket construction. A limited number of channels also reduces hardware requirements and lessens the computational burden on the myoelectric controller.

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