A VIRTUAL ENVIRONMENT ASSESSMENT OF A NOVEL PATTERN RECOGNITION BASED MYOELECTRIC CONTROL SCHEME

Levi Hargrove, Erik Scheme, Kevin Englehart and Bernie Hudgins
Institute of Biomedical Engineering, University of New Brunswick, Fredericton, Canada

ABSTRACT

This work compared a novel pattern recognition based myoelectric control system to a system based on conventional control and another state-of-the-art pattern recognition system. The results showed that the proposed system provides a more usable system as assessed qualitatively and quantitatively through a modified virtual clothespin test. Furthermore, the proposed system was designed to have an intuitive clinician interface and should help facilitate the acceptance of pattern recognition based myoelectric control systems in the clinic.

INTRODUCTION

Pattern recognition based systems have demonstrated the ability to discriminate between many different degrees of freedom (DOFs) with a high degree of accuracy in controlled laboratory experiments; however, they have yet to receive widespread clinical acceptance. An intuitive configuration interface which provides feedback about the DOFs under control is a necessity for its acceptance. Furthermore, the control system must demonstrate good classification accuracy of intended motions and, more importantly, real-time controllability.

All pattern recognition based myoelectric control systems operate on the assumption that at a given electrode location, the set of features describing the myoelectric signal will be repeatable for a given state of muscle activation and different from one state of activation to another [1]. The problem is then reduced to representation of the MES signal, mapping the raw MES to feature space, followed by discrimination/classification of that space for the various motions. This work introduces a novel pattern recognition based myoelectric control scheme based on parallel binary classifiers. The system was assessed using a clothespin test implemented in a virtual environment and compared to a conventional control system based on mode switching and another state-of-the-art pattern recognition system.

BACKGROUND

Parallel binary classifiers have been used in previous pattern recognition problems [2]; however, not explicitly in the context of myoelectric control. The proposed control scheme, termed a multiple binary classifier (MBC) is based on uncorrelated linear discriminant analysis (ULDA) feature reduction [3] prior to one-versus-all classification [2].

Linear Discriminant Analysis (LDA) is a well known signal processing tool for classification and dimensionality reduction. Given a set of high dimensional data grouped by classes, LDA provides an optimal linear transformation to a lower dimensional manifold by simultaneously minimizing the within class distance and maximizing between class distance. ULDA further constrains the LDA algorithm such that the resulting transformations are uncorrelated, thus ensuring that the LDA algorithm converges even for the cases of non-singularity within class scatter matrices. A mathematical derivation and efficient algorithm for performing ULDA feature reduction was given by Ye et al [3]. An important property of the ULDA algorithm is that it will yield at most C-1 linearly independent features, where C is the number of classes in the data.
In one-versus-all classification, a separate classifier is made for each class, with classes being grouped as the target class and all other classes. This is best demonstrated through a simple conceptual example.

![Diagram of one-versus-all classification](Image)

**Figure 1:** Conceptual Example of one-versus-all Feature Reduction. The classes (A, B, and C) are grouped into the desired class (Class 1) and all other classes (Class 2). The classifiers for classes A and B are shown. The classifier for Class C would be constructed in the same manner. The ULDA single discriminatory feature is also shown for each classifier.

When the number of classes is reduced to two using one-versus-all classification, ULDA feature reduction may be used to visualize the single discriminatory feature. If the classes are linearly separable, an adjustable threshold can be set to separate the data. The patterns are projected down the set of ULDA feature reduction matrices in parallel to determine the appropriate class as shown in Figure 2.

![Diagram of ULDA transformations](Image)

**Figure 2:** Parallel projections of patterns down the ULDA transformation matrices. Patterns located in the proper feature space regions are identified as the appropriate class.

If two or more of the binary classifiers produce outputs corresponding to their active class, there is a strong indication that the MBC has made an error and the safest course of action is to map the output to 'no motion'. The previous conceptual example is admittedly simple, but the technique should generalize to N-dimensional space provided the features are linearly separable.
METHODS

The proposed MBC classifier was assessed using a modified virtual clothespin test [4] and was compared to a conventional control (CON) system with mode switching and another state-of-the-art pattern recognition based myoelectric control system based on multi-class linear discriminant analysis (LDA) [5]. 12 normally limbed subjects completed the usability test with each of the control systems on separate days. The usability test required that the subjects have control of the wrist flexion/extension, wrist rotation, and hand open and close DOFs. For the conventional control system, electrodes were placed over the wrist flexor and wrist extensor muscle groups. A mode switch, operated using the subjects opposite arm, was used to toggle through the DOFs. For the pattern recognition systems, 8 electrodes were placed at equidistant locations around circumference of the forearm. Training and test data were collected in guided sessions using the UNB Acquisition and Control Environment (ACE) [6].

After the control system was trained, the user entered the virtual environment and was allowed to practice operating the limb. The clothespin test, a simulation of the real-world assessment technique, is a modified version of the one used by Lock [4]. Starting from a neutral position, the user is required to pick up a clothespin from a horizontal bar and move it to a vertical bar. When the hand is in position and closed over the clothespin, the pin turns red and is picked up. When the pin is positioned properly on the vertical bar, it turns green and the user can open the hand to release the pin. If the user opens the hand when the pin is not position, the pin drops and a new one appears on the horizontal bar. One clothespin test trial consisted of moving three clothespins from the horizontal bar to the vertical bar. The average time taken to move each pin and the total number of pin drops were recorded for each trial. The subjects were given one ‘orientation’ trial during which they were coached on where to position the hand to pick up and drop off the clothespin. After the orientation, subjects completed 8 clothespins trials with each control scheme. The metrics recorded were the average time taken to move clothespins during each trial and the number of clothespins dropped. The subjects were also observed and assessed qualitatively by the experimenter as they completed the test. Furthermore, offline classification accuracies were found for the pattern recognition systems to investigate a relationship between classification accuracy and usability.

RESULTS AND DISCUSSION

Table 1 displays the average pin placement times, the standard deviation of the pin placement times between subjects, and the total number of pins dropped and classification results for all subjects for each of the control schemes.

<table>
<thead>
<tr>
<th>Control Scheme</th>
<th>CON</th>
<th>LDA</th>
<th>MBC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Placement Time (s)</td>
<td>28.6</td>
<td>27.2</td>
<td>21.4</td>
</tr>
<tr>
<td>STDev Time (s)</td>
<td>8.7</td>
<td>12.1</td>
<td>7.4</td>
</tr>
<tr>
<td>Total Drops</td>
<td>8</td>
<td>29</td>
<td>1</td>
</tr>
<tr>
<td>Classification Error (%)</td>
<td>N/A</td>
<td>2.6</td>
<td>4.9</td>
</tr>
<tr>
<td>STDev Error (%)</td>
<td>N/A</td>
<td>1.7</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Table 1: Results of the Virtual Clothespin Usability Study
It should be noted that results presented are for trials 5-8 for each subject because the subjects exhibited a learning effect during the first 4 trials, but very little learning thereafter. A statistical ANOVA showed that the MBC had significantly lower pin placement times ($p<0.001$) but a significantly higher classification error ($p<0.001$). A statistical analysis was not completed on pin drops, but it is apparent that the MBC classifier yielded fewer pin drops than the CON and LDA systems.

A scatter plot of the classification error and pin placement times is shown in Figure 3.

![Scatterplot of Time vs Classification Error](image)

**Figure 3:** Scatter plot of average placement time vs classification error for the pattern recognition systems.

A positive correlation between classification error and pin placement time was observed for both control schemes. The main observation was that the classification error metric for each classifier is computed in the same manner; however, the slope of the regressions lines differs. This implies that classification error does impact usability but that there are additional factors as well. The number of data points in the scatter plot is limited and addition data should be collected before stronger conclusions may be drawn.

The following paragraph summarizes the qualitative observations made during the experiment. Firstly, subjects disliked the mode switched conventional control because they found it difficult to keep track of which mode was next in the sequence. Subjects could easily operate the DOF once they were certain which mode they were in. Another criticism of the conventional control scheme was that contractions were not physiologically appropriate and some had difficulty remembering that wrist flexion could operate hand close or wrist pronation depending on the active mode. Subjects generally preferred the MBC and LDA control schemes over the conventional based system. Most subjects found it more intuitive to use because the control was physiologically appropriate and a mode switch was not required. The MBC control scheme had a higher classification error, but in all cases the majority of errors were ‘no-motion’ errors meaning the prosthesis did not operate. The majority of LDA classification errors were errors to other ‘active’ classes. These inadvertent activations were very problematic for most subjects and led to slower pin placement times because the subject had to correct the error before continuing with the test. Inadvertent activations were also to blame for the majority of pin drops noted with the LDA classifier; the hand would often involuntarily open when the subject was trying to extend the wrist. All three control systems were criticized for not providing...
simultaneous control over multiple DOFs. The virtual environment was also criticized for a lack of depth perception and slow rendering time.

CONCLUSIONS

The MBC control scheme is a novel pattern recognition based myoelectric control system which was designed to have a clinically intuitive interface. After training data is collected, the clinician can set a series of thresholds for each DOF in a similar manner as is done with current conventional control systems. The MBC control system yielded faster clothespin placement times when compared to a conventional control based system and another state-of-the-art pattern recognition system. Furthermore, the majority of the subjects stated a preference for the MBC control system during usability testing.

REFERENCES


