An Adaptive Classification Methodology for Myoelectrically Controlled Prostheses

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INTRODUCTION

For amputees and individuals with congenital deficiencies of the upper limbs, powered prosthetic devices can restore a level of functionality that is close to natural motion. In order for this to occur, an effective input signal to the control system of the limb is necessary. Previous studies have shown that myoelectric signals (MES) are effective as inputs [1, 2]. One of their benefits of using MES as input control signals is that they can be easily and non-invasively monitored using surface electrodes on the skin.

Pattern classification techniques have been successfully used to classify MES inputs to particular prosthetic output motion, with classification accuracies of approximately 95% for a six class problem [2]. Pattern classification techniques classify data by comparing them to templates formed by a set of training exemplars; however, over time changes occur in the MES measurement conditions (e.g. electrode contact characteristics, electrode position) and the method by which a user actuates a particular motion.

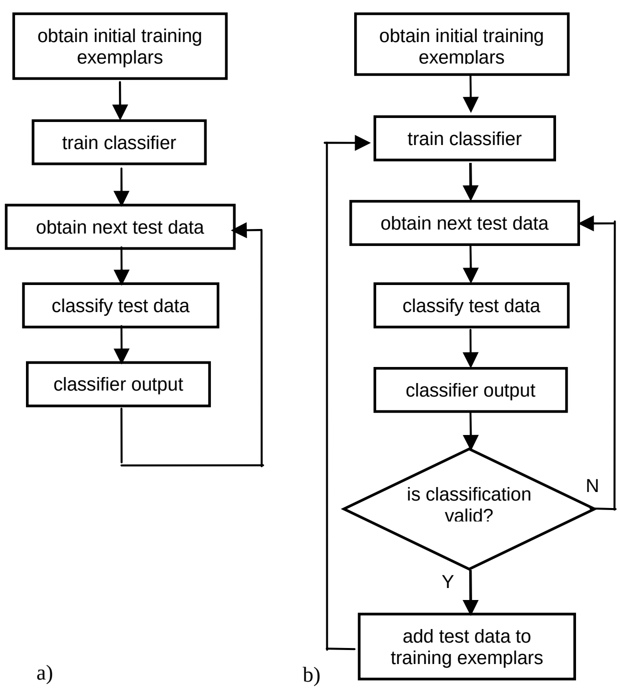

Figure 1. Block diagram of a) a non-adaptive classifier and b) an adaptive classifier.

These changes lead to an increase in signal variation between the test data (i.e. the data to be classified) and training data, which in turn causes a decrease in classification accuracy.

To dynamically adapt to the changing MES, this study proposes a continuously trained or “adaptive” classifier which improves classification accuracy through continuous online training. Figure 1 compares the functionality of an adaptive classifier with a non-adaptive (non-continuously trained) classifier.

Both classifiers use a set of training data to initially train the classifier. The input signal is partitioned into windows of equal size and a set of features is extracted from each window, forming a feature vector. With training data, the limb motion associated with each data window is known, so a template can be formed from the feature vectors for each class.

In its on-line operation, the non-adaptive classifier classifies test feature vectors by comparing them with templates formed by from a static set of training exemplars. In contrast, the adaptive classifier continuously updates the training exemplars with new incoming data. In its on-line operation, the current MES input is classified by comparing it to the templates formed by the training exemplars, as in this non-adaptive classifier. The measure of the validity of the decision is determined, and if there is high confidence that the decision is valid (i.e correct), it is used as a target class label and the associated data are incorporated into the training set for that target. Older training data are discarded, enabling newer data to be used for retraining, thereby allowing the classifier to adapt to changes in the MES as they occur.

Ideally, the adaptive classifier only uses correctly classified feature vectors for retraining. Incorporating incorrectly label test data will likely result in an increase in classification error. If misclassifications can be avoided, the adaptive classifier should see an increase in classification accuracy as the classifier is able to adjust to changing conditions.

METHODOLOGY

Data Collection

Data were collected from eight MES control sites, using Ag-AgCl Duotrode electrodes (Myotronics, 6140). An Ag-AgCl Red-Dot electrode (3M, 2237) was also placed on the wrist to provide a common ground reference. Signals were amplified (Grass Telefactor, Amplifiers M15A54), with the variable gain set at 1000 and a bandwidth of 1 Hz to 1000 Hz. Signals were then sampled at 3000 Hz using a 12-bit analog-to-digital converter board (National Instruments, PCI-6071E). These signals were downsampled offline to a sampling rate of 1000 Hz.

Data were collected from twelve normally limbed subjects (6 males, 6 females). Each subject underwent four data collection sessions over separate days, within a one week period. To avoid large changes in electrode placement between sessions, permanent marker was used to indicate the electrode locations. Each session consisted of six distinct trials, where subjects performed seven limb motions in a random order with the elbow maintained a 90° flexion: wrist flexion, wrist extension, supination, pronation, palm open, palm closed, and rest. Each motion was held for three seconds and repeated four times within each trial (approximately 90 seconds/trial). A short rest period (approximately one minute) was given between each trial.

Data from session 1 was thought to have greater signal variation as the subject became accustomed to the data collection method. This session was considered a learning session and its data were discarded. Data from session 2 were used as initial training data, and data from sessions 3 and 4 were used as test data.

Classification

MES data were segmented into overlapping 256 ms windows, spaced 32 ms apart. For each window, the root-mean-square (RMS) value and the first four autoregressive (AR) coefficients were computed as signal features. Training feature vectors were taken at equal intervals from the training set (session 2).

Data were classified using linear discriminant analysis (LDA). In this classification technique, an estimate of the probability density function (pdf) was made for each class (λ_i; i = 1, 2, …, 7). The pdf was constrained to a multivariate Gaussian pdf (i.e. $\eta(\mathbf{x},\mu_i,\Sigma_i)$), so the pdf could be estimated by simply computing the mean vector (μ_i) and covariance matrix (Σ_i) from the training data. A simple training algorithm for the classifier is paramount so that retraining can be done in real-time. An unknown signal from the test data $\mathbf{x}$ could be classified by choosing the class associated with the pdf that has the highest *a posteriori* probability of generating $\mathbf{x}$, that is,

$$\arg\max_{i} p(\mathbf{x} \mid \lambda_i) \tag{1}$$

In [3], it is noted that producing class decisions every 32 ms is much faster than what a prosthetic limb could respond to. Excess decisions are still useful, however, as they can be combined using a majority vote algorithm to help eliminate spurious misclassifications. Using a similar approach as in [3], a majority vote was implemented using nine elementary decisions, which included the current decision, along with the previous eight decisions.

In [3] it was also noted that many classification errors occur during transitions between classes. This error is expected because the MES is in an undetermined state between contraction types. This error is also considered acceptable as it is doubtful that a prosthesis would be able to respond to transitory misclassifications due to mechanical inertia. To avoid transitory data, 256 ms before the start and 32 ms at the end of each limb motion was removed from the initial training set. To account for this type of misclassification in the test set, classification accuracies were computed eliminating the 256 ms period at the start of each limb motion in the test data.

Optimization of the Adaptive Classifier

The adaptive classifier must determine the validity of the current decision in order to decide whether it should be used to retrain the classifier. To do so, a retraining buffer is employed (Figure 2). It was assumed that all classifications in a full retraining buffer were correct.

The retraining buffer was used to maintain the current class decision and the previous M identical, consecutive majority vote classifications. If the current decision differed from the decisions in the buffer, then the buffer was emptied and restarted with current decision. Retraining occurred only when the buffer was full, and feature vectors were selected from it at a particular interval.

Three parameters which affected the accuracy of the adaptive classifier were identified. These were:

1. The size of the training buffer: Initial training for both the non-adaptive and adaptive classifiers was done using a set of exemplars from the training set. The training buffer contains the feature vectors used to produce the pdfs for each class. In the non-adaptive classifier, the training vectors do not change during classification. In the adaptive classifier, older training vectors are discarded when new vectors are added for retraining, maintaining the size of the training buffer. With a large training buffer, the addition of new vectors would have little effect as the majority of training vectors would remain the same. A smaller training buffer

would cause a greater change in the pdfs, since more of the older vectors would be discarded.

2. The size of the retraining buffer: Since retraining occurs only when this buffer is full, a value must be chosen so that there is high confidence that the decisions in the buffer are correct. A small buffer will result in more retraining; however, it is possible that there are a number of consecutive misclassifications which will increase classification error if used in retraining. Less retraining would occur if a larger buffer were implemented, although there is a higher confidence that those classifications will be correct (i.e. less chance of a large number of consecutive misclassifications).
3. The interval at which feature vectors are chosen for retraining from the retraining buffer: Even though all decisions in the full retraining buffer are assumed to be correct, retraining on every feature vector may have a detrimental effect on classification accuracy if this assumption is wrong. Therefore, only certain feature vectors are chosen to be incorporated into the training set. A small interval selects more feature vectors and causes the pdf to change quickly; a larger interval chooses less feature vectors and the pdf changes more gradually.

In order to determine the optimal value for each parameter, six subjects were chosen to test various combinations of the parameters (Group A). These six were chosen because they had initial non-adaptive classification errors of less than 15%. Using the adaptive classifier with these subjects should produce less classification errors since most of the classifications are correct and retraining on correct classifications produces a more accurate pdf representation of the MES. Once the optimal parameters were determined, the remaining six subjects (Group B) were classified using the adaptive classifier to evaluate the general applicability of this new methodology. Because error rates for the remaining subjects were already high with the non-adaptive classifier, it is expected that the adaptive classifier will not have as great an effect on the results. Retraining may occur on misclassifications, which will have a negative effect on the accuracy.

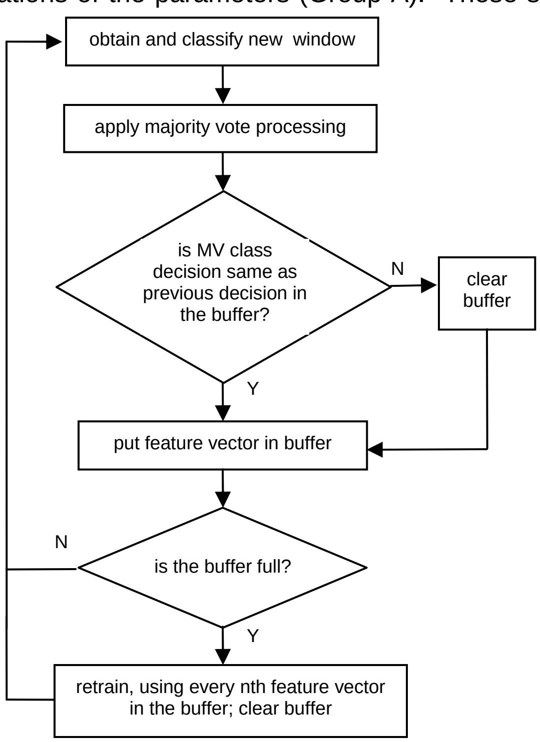

Figure 2 – Implementation of the retraining buffer

RESULTS

It was found that the optimal combination of parameters for the adaptive classifier was a training buffer size of 1408 feature vectors and a retraining buffer size of 64 with every 8th feature vector being used for retraining from the full buffer.

Table 1 summarizes the classification errors for the adaptive classifier compared to the non-adaptive classifier for Group A.

Table 1
Classification Errors for Group A Subjects

Subject	Non-adaptive	Adaptive
1	6.00 %	5.54 %
2	8.03 %	6.42 %
3	9.92 %	6.25 %
4	12.54 %	9.79 %
5	5.96 %	4.10 %
6	10.18 %	5.09 %
Average	8.77 %	6.20 %

Each of these subjects shows an improvement when using the adaptive classifier. A two-tailed paired t-test shows that the difference between the classification errors of the two classifiers is significant ($p = 0.012$).

Table 2
Classification Errors for Group B Subjects

Subject	Non-adaptive	Adaptive
7	12.54 %	15.68 %
8	30.00 %	38.38 %
9	26.80 %	27.13 %
10	24.99 %	29.19 %
11	18.88 %	17.45 %
12	22.28 %	19.75 %
Average	22.58 %	24.60 %

Table 2 summarizes the classification errors for Group B. For two of the subjects (subjects 11 and 12), the adaptive classifier had better results; for the rest, the adaptive classifier had higher error, most likely due to retraining on misclassifications. The difference between the errors is not significant (p = 0.277).

DISCUSSION

As expected, the Group A subjects all had lower classification errors when using the adaptive classifier. Because the initial non-adaptive classifier errors were low, the adaptive classifier would most likely retrain using correct class decisions. This would cause the change in the pdf to accurately reflect the changes in the MES, and subsequent classifications of the test signal would be correct. This is illustrated in Figure 3, which shows some of the classifications for subject 5. Figure 3a shows the results of the non-adaptive classifier; while some misclassifications do occur, they are relatively few and only in the transition periods. Figure 3b shows the results of the adaptive classifier; retraining occurs using correct classifications.

In contrast, Group B subjects had varied results. When the initial error rate is high, retraining can occur using misclassifications, which causes an increase in error. Figure 4 shows the non-adaptive and adaptive classification results for Subject 8. Using the non-adaptive classifier, several misclassifications are made (Figure 4a). Retraining occurs using some of the misclassifications (Figure 4b); in this case, the pdf of class 5 will undergo a drastic change, whereas the pdfs of the classes to which the windows should have been classified will not change enough to adapt to the MES.

Although Group B performed relatively poorly using the adaptive classifier, when subject 8 is removed from the data set, the classification averages for the non-adaptive and adaptive classifiers are 21.10% and 21.84%, respectively. With the removal of this single subject, the adaptive classifier is comparable to the non-adaptive classifier, even when initial error rates are high.

CONCLUSION

MES were classified using a non-adaptive classifier and an adaptive classifier which utilized a retraining buffer to determine classification validity. Two groups of subjects were tested: Group A, which had initial non-adaptive error rates of less than 15% and Group B, with higher initial error rates. The adaptive classifier improved accuracy in Group A by 2.57%. Accuracy decreased in Group B by 2.02%; however, their difference is not statistically significant and when the result from the worst subject is removed, the decrease is only 0.64% on average for the remaining subjects.

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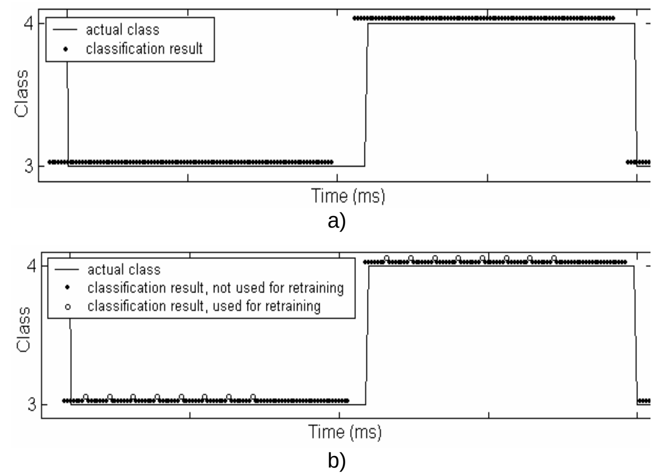

Figure 3 – Classification results for Subject 5 using a) non-adaptive and b) adaptive classifier.

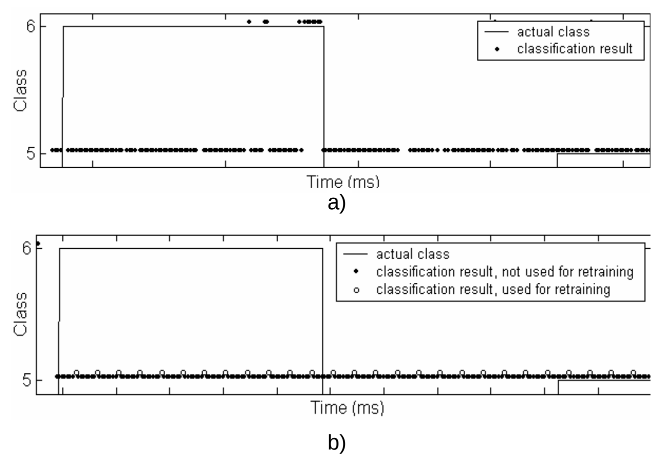

Figure 4 – Classification results for Subject 8 using a) non-adaptive and b) adaptive classifier.