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Analysis of Electrode Shift Effects on Wavelet Features Embedded in a Myoelectric Pattern Recognition System

Juan M. Fontana, PhD^{1,2,*} and Alan W.L. Chiu, PhD^{2,3}

¹Department of Electrical and Computer Engineering, The University of Alabama, Tuscaloosa, AL, United States

²Biomedical Engineering Department, Louisiana Tech University, Ruston, LA, United States

³Applied Biology and Biomedical Engineering, Rose-Hulman Institute of Technology, Terre Haute, IN, 47803, United States

Abstract

Myoelectric pattern recognition systems can translate muscle contractions into prosthesis commands; however, the lack of long-term robustness of such systems has resulted in low acceptability. Specifically, socket misalignment may cause disturbances related to electrodes shifting from their original recording location, which affects the myoelectric signals (MES) and produce degradation of the classification performance. In this work, the impact of such disturbances on wavelet features extracted from MES was evaluated in terms of classification accuracy. Additionally, two principal component analysis frameworks were studied to reduce the wavelet feature set. MES from seven able-body subjects and one subject with congenital transradial limb loss were studied. The electrode shifts were artificially introduced by recording signals during six sessions for each subject. A small drop in classification accuracy from 93.8% (no disturbances) to 88.3% (with disturbances) indicated that wavelet features were able to adapt to the variability introduced by electrode shift disturbances. The classification performance of the reduced feature set was significantly lower than the performance of the full wavelet feature set. The results observed in this study suggest that the effect of electrode shift disturbances on the MES can potentially be mitigated by using wavelet features embedded in a pattern recognition system.

Keywords

Electrode shifts; feature extraction; myoelectric control; principal component analysis; support vector machines; wavelet decomposition

INTRODUCTION

In the United States, two million people live with limb loss and it is projected that this number will grow more than twice by the year 2050 (Ziegler-Graham, MacKenzie, Ephraim,

*Corresponding author. Mailing Address: 101 Houser Hall, Tuscaloosa, AL, United States. 35487-0286. jmfontana@bama.ua.edu; juanmfontana@gmail.com.

Travison, & Brookmeyer, 2008). Even though lower limb amputations are 20 times more frequent than upper limb amputations, the damage produced by the loss of the upper extremity is much more significant (Baumgartner, 1992) because the dexterity of the hand plays a major role in carrying out the different activities of daily living. Individuals suffering of an upper-limb amputation have a need of comfortable, functional, and cosmetic prosthetic devices. However, current prostheses are mostly focused on one of these attributes so they do not present an appropriate balance among them, which may be the reason of the high rejection rate (Biddiss & Chau, 2007; Pylatiuk, Schulz, & Döderlein, 2007).

Currently, the use of myoelectric signals (MES) as the control strategy of prostheses (Oskoei & Hu, 2007; Parker, Englehart, & Hudgins, 2004, 2006) offers a viable alternative for body-powered control by providing more functionality and better cosmetic appearance as signals recorded during voluntary muscle contractions are translated into different prosthetic actions (Castellini & Van Der Smagt, 2009; Zecca, Micera, Carrozza, & Dario, 2002). Through the implementation of myoelectric pattern recognition systems, multiple actions can be created by discriminating different muscle states. Many myoelectric pattern recognition (Al-Assaf, 2006; Englehart & Hudgins, 2003; Martelloni, Carpaneto, & Micera, 2009; Park & Lee, 1998) and feature extraction algorithms (Chu, Moon, & Mun, 2006a; Englehart, Hudgins, Parker, & Stevenson, 1999; Guler & Kocer, 2005; Hu, Wang, & Ren, 2005; Hudgins, Parker, & Scott, 1993; Zardoshti-Kermani, Wheeler, Badie, & Hashemi, 1995) have been proposed for real-world prosthetic applications. Although successful performances were obtained on able-body subjects and amputees under laboratory settings, several obstacles need to be addressed before achieving a high clinical acceptance level. One of the main barriers is the lack the long-term robustness due to misalignment of the prosthesis' socket with respect to the residual limb which may cause a shift in the electrode recording locations and consequently a degradation of the system performance (L. Hargrove, Englehart, & Hudgins, 2008).

Several studies have analyzed the effect of electrode shift on myoelectric pattern recognition (L. Hargrove, Englehart, & Hudgins, 2006; L. Hargrove et al., 2008; Hudgins et al., 1993; Tkach, Huang, & Kuiken, 2010; Young, Hargrove, & Kuiken, 2011). Classification accuracy has been the parameter chosen to evaluate changes in the performance of such systems when electrode shifts were artificially introduced. One of the studies concluded that the classification accuracy is significantly reduced when the magnitude of the electrode displacement in any direction is larger than the magnitude of the EMG pickup area (L. Hargrove et al., 2006). This accuracy reduction was irrelevant when the electrodes were widely spaced but in a nontraditional electrode orientation (Hudgins et al., 1993). An alternative solution is to train the system at all expected displacement locations, however this solution requires substantial amount of time and effort (L. Hargrove et al., 2008). A recent study investigated changes in electrode size and orientation to reduce the classification error (Young et al., 2011). When electrode displacements were introduced, the electrodes oriented parallel to the muscle fiber presented a significantly better performance than electrodes oriented perpendicular. Larger electrodes helped to reduce classification accuracy sensitivity but only for shifts perpendicular to the muscle fibers. Another study analyzed the stability of the signal features during changes in the MES caused by three different types of disturbances: electrode location shift, muscle fatigue and variations in

muscle contraction efforts (Tkach et al., 2010). For the most stable set of features, electrode location shifts produced a significant drop in classification accuracy from 90% to 72.6% when classifying 4 classes. All of the studies described in this paragraph used time-domain (TD) features to represent the MES waveform due to their low computational complexity

In this work, we investigated the use of wavelet features extracted from the MES by performing multi-resolution Analysis (MRA) to mitigate the effect of electrode shifts. Numerous studies used wavelet features to classify muscle contractions achieving high classification accuracies; however, to the best of our knowledge, no one has considered potential variations in the original electrode locations (Boostani & Moradi, 2003; Wang, Wang, Chen, & Zhuang, 2006; Wang, Yan, Hu, Xie, & Wang, 2006). The ability of the wavelet basis to model the elemental motor unit action potentials of the steady-state MES makes this method appropriate for myoelectric pattern recognition (Englehart, Hudgin, & Parker, 2001). Even though the computational complexity of wavelet features may be higher than TD features, the real-time implementation of a wavelet-based myoelectric pattern recognition system is not jeopardized. Additionally, two principal component analysis (PCA) frameworks were used to reduce the dimension of the wavelet feature vector which may benefit the entire pattern recognition system by reducing the model complexity. Several studies have used PCA for extraction and dimensionality reduction of MES features showing an improvement in classification accuracy but without considering potential electrode shifts (Chu, Moon, & Mun, 2006b; Englehart et al., 1999; L. J. Hargrove, Li, Englehart, & Hudgins, 2009). The dimensionality reduction methods proposed in the present work were evaluated with the goal of maintaining or improving classifier performance when electrode shifts are included in the training data while reducing the computation time or model complexity related to dimensionality of the dataset.

This paper continues with the Methodology section, which presents a detailed description of the signal recording, feature extraction, signal classification, and dimensionality reduction methodology. The Results section presents the major results of the electrode location shifts incidence on full and reduced set of wavelet features. The Discussion section presents a more detailed analysis of the results and implications of this study. The Conclusion section finishes this paper.

METHODOLOGY

Data Collection and Signal Conditioning

MES were recorded from seven able-body subjects (four males, three females, age 19–28 years old) and one female subject (age 21 years old) with below-elbow congenital limb loss. The study was approved by the Louisiana Tech University Institutional Review Board and subjects signed an informed consent form before each experiment. The MES were collected using BioRadio 150 wireless data acquisition system (CleveMed, Inc.). For the able-body subjects, seven bipolar channels oriented parallel to muscle fibers were distributed along five selected forearm muscles mostly responsible for the wrist movements (Figure 1, left). One pair of Ag/AgCl electrodes (Vermed, Inc.) were placed on the *Extensor Digitorum*, *Anconeus*, and *Flexor Carpi Ulnaris* muscles and two pairs of electrodes were placed on the *Extensor Carpi Ulnaris* and the *Flexor Carpi Radialis* muscles. For the subject with

below-elbow congenital defects, six bipolar electrodes were circumferentially distributed around the residual forearm whereas the seventh channel was placed on the stump as illustrated in Figure 1, right.

MES for each subject were collected on six different recording sessions occurring at different days of the week. At the beginning of each session, a detailed protocol was followed by a member of the research team to find each muscle under study and to identify the precise location of the electrodes (original location). For example, subjects were asked to perform a specific hand movement to locate the Flexor Carpi Ulnaris muscle, where the original location of a pair of electrodes was at approximately 40% of the line extended from the origin of the muscle to the end of it (corresponding to the thickest cross section area of the muscle). Similar procedures were followed to identify the rest of the original locations of the electrodes. Once they were found, a shift in the location of each pair of electrodes was randomly introduced before beginning the recording session. These shifts were of up to 2 cm away from the original position and in any direction. The rationale for incorporating this variability in the data is to mimic the misalignment of the prosthesis' socket as the result of long term use of the prosthetic device.

During each session, subjects were asked to perform four types of wrist movements involving the isometric contraction of the forearm muscles: *abduction*, *adduction*, *extension*, and *flexion*. A total of 125 seconds of myoelectric signals representing each motion were stored as a result of 25 repetitions of 5 seconds duration each, with 3 seconds of resting intervals between repetitions and at least 1 min resting every 5 repetitions to reduce muscle fatigue. Additionally, 120 seconds of no muscle contraction signals (rest) were recorded.

In the conditioning stage, the signal sampled at 960Hz was filtered using both a tenth order high-pass Butterworth filter (20Hz cutoff frequency) and a notch filter (60Hz). The amplitude of the resultant signal was normalized with respect to the signal maximum value to compensate for changes in amplitude between channels. The normalized signal was then segmented into non-overlapping 256-point windows.

Feature Extraction

A previous study showed that the stability of TD features was affected by electrode shifts causing a reduction in accuracy (Tkach et al., 2010). Wavelet features may overcome the behavior of TD features when the same type of disturbances affects the MES due to the ability of wavelet functions to resemble the motor unit action potentials that represent the gross MES (Chu et al., 2006b). Wavelet features may have higher computational complexity than TD features but the real-time implementation of a myoelectric pattern recognition system is not jeopardized. Consequently, discrete wavelet transform was applied to each of the 256-point moving time window for feature extraction. Given the discrete vector $y(n)$ with $n=1, 2 \dots N=256$ representing the MES in each time window, the wavelet transform mapped this vector into a set of wavelets coefficients. For this study, 4 levels of wavelet decomposition were applied to each MES window to obtain wavelet coefficients representing 5 frequency sub-bands. Second order Coiflet was the mother wavelet used in all cases (Al-Assaf, 2006; Englehart et al., 2001). The frequency ranges represented by the wavelet coefficients depend on the frequency at which the signal was sampled. In this

particular study, the sample frequency was 960 Hz, which implied that the approximation coefficients for 4 decomposition levels represented the 0 – 30 Hz frequency range. Further decomposition of the approximation coefficients would not add relevant information to the feature set as most of the information in the MES is grouped in frequency components greater than 30Hz (De Luca, Donald Gilmore, Kuznetsov, & Roy, 2010). The wavelet feature vector was then created by computing the average energy of the wavelet coefficients at each frequency sub-band. Finally, features from the seven channels were grouped into a 35-dimension feature vector.

Dimensionality Reduction

Principal Component Analysis (PCA) is one of the more commonly used techniques for feature reduction. It orthogonally projects multivariate data into a new coordinate system (feature space) such that the variance of the projected data is maximized (Bishop, 2006).

In this study, PCA was applied to the wavelet feature set for dimensionality reduction. Since the solution for the multiclass classification problem was approached by training multiple binary classifiers and organizing them in a tree structure (explained in the Signal Classification section), two different methods involving PCA were implemented to project the wavelet features. First, in the method named ‘Global PCA’ hereafter, a single feature space was associated with the entire tree (Figure 2, left). The projection matrix for this feature space was obtained by calculating the eigenvalues and eigenvectors of the training set. Wavelet features were linearly projected to the new feature space before training and testing the classifiers. Second, in the method called ‘Local PCA’ hereafter, one feature space was associated to each binary classifier (node) on the tree (Figure 2, right). The projection matrix for the feature space associated with binary classifier i -vs- j was created by calculating the eigenvectors and eigenvalues of the training set formed by wavelet features from classes i and j only. As depicted in Figure 2, right, a total of 10 feature spaces for the whole tree were obtained. In this case, the binary classifier i -vs- j was trained using the projected features belonging to classes i and j . In the testing stage, wavelet features representing a test data were projected before entering a binary decision node.

To determine the most appropriate M dimensional feature subset for both Global PCA and Local PCA, each PCA method was applied to the MES data from one recording session. In this stage, the training set consisted of the first 100 seconds of each contraction type and the first 100 seconds of the rest state. The testing set consisted of the remaining 25 seconds of each contraction and the remaining 20 seconds of the rest state. One multiclass classifier was trained for $M = 10, 11, \dots, 35$. The dimension of the reduced feature set was given by the lowest M such that the classification performance of a M dimensional feature set was not significantly different from the performance of a $M = 35$ dimensional (unreduced) feature set (two tailed t-test, with significance level $p = 0.05$).

Signal Classification

Support Vector Machines (SVM) is a machine learning algorithm that maps the input data into a high dimension linearly-separable feature space (Cortes & Vapnik, 1995). The rationale for selecting SVM in this study was that the robustness and high generalization

property of SVM become beneficial when classifying data with high variability as it is the case of the MES affected by electrode shift disturbances. The Radial Basis Function (RBF) kernel was used because of its ability to map the input vector into an infinite dimension increasing the chance of obtaining good data separation in the new space. The most appropriate values for the kernel parameter γ and the regularization coefficient C were selected by a grid search procedure for $\gamma \in (1^{-4}, 1^{-3}, \dots, 1^0)$ and $C \in (2^{-1}, 2^0, \dots, 2^9)$.

Multiclass SVM classifiers were trained in this study to discriminate among $N = 5$ classes (abduction, adduction, extension, flexion and rest). The decision-directed acyclic graph (DAG) method (Platt, Cristianini, & Shawe-Taylor, 2000) was chosen to perform multiclass classification. In the training stage, one binary classifier was constructed for each pair of classes, leading to a total of 10 binary classifiers. In the testing phase, the resulting DAG tree was used to classify each point in the test set.

Analysis of Electrode Shifts Effects

The effect of shifts in electrode locations on the wavelet feature set without reduction (DWT), and on both Global PCA and Local PCA feature sets was evaluated by training one multiclass SVM classifier at each recording session using data from all previous sessions to incorporate variability in the training set. The classifier was tested with data from the current session. For that reason, the first classifier was trained in session 2 with data from session 1 and tested with data from session 2. Next, in the recording session 3, the training set incorporated data from sessions 1 and 2 whereas the testing set contained data from the session 3 (current session) only. The performances of the classifiers were evaluated at each recording session to compare the behavior of DWT, Local PCA and Global PCA features as more electrode shift disturbances were included into the training data.

The performance of a classifier was evaluated using the classification accuracy defined as the total number of points that were correctly classified divided by the total number of points. For able-body subjects, results are presented in terms of the average classification accuracy, which is the mean accuracy achieved across all subjects. Additionally, the decision time, defined as the time required to project the features into the new feature space and to classify them using the DAG tree, was used to compare the performances of the PCA methods. A complexity analysis was also performed to determine the feasibility of each PCA method to be implemented in a real-time application.

RESULTS

Global PCA vs. Local PCA

Results of applying Global and Local PCA to MES data from a single recording session showed that no significant differences in the average classification accuracies were found for dimensions $M \geq 10$ between the two PCA methods for able-body subjects and for the subject with congenital limb loss (Figure 3 and Figure 4). Without dimensionality reduction ($M = 35$), DWT features from able-body subjects achieved a $93.84 \pm 3.64\%$ accuracy averaged across all able-body subjects (82.79% for subject with congenital limb loss), Local PCA features reached an average accuracy of $92.67 \pm 4.77\%$ across all able-body subjects

(82.79% for subject with congenital limb loss) and Global PCA features a total of $93.59 \pm 4.04\%$ accuracy averaged across all able-body subjects (80.98% for subject with congenital limb loss). A reduction in the dimensions of the training vectors by either Global or Local PCA was associated with a reduction in the classification accuracy for both able-body subjects and subject with limb loss. Statistical results also showed that the dimension of the wavelet feature vector can be reduced from $M = 35$ to $M = 18$ using Global PCA and to $M = 24$ using Local PCA without significant drop in the average classification accuracy.

Electrode Shift Effect

Figure 5 and Figure 6 show the performances of the SVM classifiers trained at different recording sessions for both able-body subjects and for subject with congenital limb loss, respectively. For able-body subjects (Figure 5), there was a significant increase in accuracy from session 1 to session 2 (two-tailed t-test, $p < 0.05$), but no significant change was found afterwards. For Global PCA features, the highest classification accuracy was 84.68% (averaged across subjects) after features from 4 recording sessions were included in the training set. For Local PCA features, the classifier performance was steadily improving as more training data was added, showing a maximum accuracy of 84.63% (averaged across subjects) in session 6. In the last session, the training set comprised features from the previous 5 sessions and DWT features presented the highest classification accuracy of 86.5% (averaged across subjects), although this value was not statistically different with the values found for Local and Global PCA features (ANOVA with significance level $p = 0.05$).

Data from the subject with congenital limb loss showed that classification accuracy for Local PCA and Global PCA increased after the first session (Figure 6). Global PCA accuracy continued increasing as more electrode shift disturbance was added to the training set reaching the maximum of 70% at session 5. On the other hand, Local PCA accuracy did not increase after it reached the maximum at session 3. The wavelet features without reduction performed better than Local and Global PCA although statistically significant results cannot be stated. A maximum accuracy of 75% was observed in the last session. A reduction in the classification performance for the subject with congenital limb loss may be attributable to factors typical to these subjects such as the condition and geometry of the muscles in the residual limb and the ability to perform the desired muscle contractions. This reduction is also consistent with the results found in the literature (Scheme & Englehart, 2011).

Figure 6, bottom illustrates the decision times (averaged across subjects) for wavelet features without reduction, Local PCA, and Global PCA features. Results showed no significant differences in decision times during sessions 2–5 (ANOVA with significance level $p = 0.05$). For able-body subjects, only in session 6 the decision time for Local PCA was significantly higher than for DWT but not lower than Global PCA (ANOVA and Multiple Comparison tests with significance level $p = 0.05$).

Complexity Analysis

The complexity of a classifier can be expressed in terms of number of operations in a microchip for a stand-alone device that are required to make a decision on a single instance

(D -dimensional vector). PCA dimensionality reduction of a vector from dimension D to dimension M requires $M \cdot D$ operations. In addition, binary classification of the reduced vector depends on the number of support vectors in the model (NSV) and on the dimension (M) of the vector as $NSV \cdot (M+2)$. Since a DAG structure was used to perform N -class classification ($N=5$), then $N-1$ binary classifications were performed before final class assignment (see Figure 2). The original dimension was $D=35$ in all cases and the reduced dimensions were $M=18$ for Global PCA and $M=24$ for Local PCA. As a result, the implementation of Global PCA required $\{M \cdot D\} \cdot \{(N-1) \cdot NSV_{gPCA} \cdot (M+2)\} = 90,720 \cdot NSV_{gPCA}$ operations to make a decision (Figure 2, left), where NSV_{gPCA} is the number of support vectors of the final SVM classifier trained with Global PCA features. On the other hand, Local PCA required $\{(N-1) \cdot (M \cdot D)\} \cdot \{(N-1) \cdot NSV_{lPCA} \cdot (M+2)\} = 362,880 \cdot NSV_{lPCA}$ operations to make a decision (Figure 2, right) where NSV_{lPCA} is the number of support vectors of the final SVM classifier trained with Local PCA features. Results showed that the average NSV_{lPCA} was 924 ($SD \pm 34$), which was higher than the average NSV_{gPCA} (834 ± 34). This result indicated that Local PCA was significantly more complex than Global PCA, which may hinder its applicability in real-time.

DISCUSSION

One barrier to clinical acceptance of prosthetic hands is the concern about the long-term robustness of the system. Over hours of use, misalignment of the socket with respect to the residual limb may cause a change in electrode recording locations. In this study, we analyzed the use of wavelet features extracted from MES and the use of two PCA frameworks to diminish the effect of electrode shifts disturbances affecting the myoelectric signal. These disturbances were artificially introduced when collecting data from six different recording sessions. From one session to another the electrodes were removed and replaced over the skin surface but at locations randomly shifted from its original position by less than 2 cm. The rationale for this procedure was to mimic the day to day use of a myoelectric prosthesis, where a subject put on the prosthesis at a certain location, which may not be the exact same location as the day before and may move in different directions over the course of the day. The implementation of a robust pattern recognition scheme that can adapt to those changes in electrode location is critical to achieve an intuitive and precise control of the prosthesis. Such pattern recognition scheme should be able to accurately translate the intention of subjects into actions of the prosthesis (high classification accuracy). Thus, a major drop in the classification accuracy ($>15\%$) due to electrode misalignment would significantly impact the control of the prosthesis.

Wavelet features, extracted after 4 levels of wavelet decomposition, achieved an average classification accuracy of $93.84 \pm 3.64\%$ without disturbances and an average accuracy of $88.33 \pm 9.73\%$ after disturbances from four different sessions were included (Figure 5). These results are comparable to previous studies where TD features were proposed to analyze the effects electrode shifts (L. Hargrove et al., 2008; Tkach et al., 2010). In one of them, a combination of 8 TD features achieved an average accuracy of $72.6 \pm 21.9\%$ when electrode shift disturbances were present. This value was significantly lower than the 90% averaged accuracy observed for the same feature set when no disturbance was present (Tkach et al., 2010). Another study showed that the combination of TD and autoregressive

(AR) features with a novel classifier training strategy was able to obtain classification accuracies of 93% (no disturbances) and 87% (with disturbances) when classifying 9 motion classes (L. Hargrove et al., 2008). This performance was similar to the performance of the wavelet features evaluated in this work; however, the system presented by Hargrove's group may provide more flexibility as it was able to classify 9 different classes.

The effects of electrode shift were also analyzed for a subset of the wavelet features reduced by two different PCA frameworks (Global PCA and Local PCA). Results showed that the classification accuracies for PCA features were lower than for wavelet features in able-body subjects and the subject with congenital limb loss (Figure 5 and Figure 6). A potential reason for this behavior may be related to the location of the recording channels. The muscles in the forearm are closely spaced, so a signal recorded from the surface has contributions from more than one muscle. When a contraction is produced, the spatial propagation of the action potentials may lead to correlated signals at different recording sites. For the able-body subjects, the selection of the recording locations was done meticulously such that they were not strongly dependent on each other. The possible redundant information was reduced; hence no significant improvement can be made using the PCA frameworks. For the subject with congenital defects, the electrodes were circumferentially placed around the stump of the residual forearm. These locations may have caused stronger correlations between signals from different channels than in the case of able-body subjects. The implementation of the PCA projection frameworks did remove that dependency but without significant changes in the classification accuracy suggesting that elimination of the redundancy of the information captured by wavelet features was not a critical factor for classifying muscle contractions.

A significant difference in computation time was observed between Local PCA and DWT features at sufficiently high feature dimensions but no significant difference was found between Global PCA features and DWT features. The main reason for the longer delay of Local PCA was possibly due to a new feature projection was done at each binary decision node in the DAG path (Figure 2, right), while in the Global PCA, the projection was only performed once (Figure 2, left). This statement is supported by the results of the complexity analysis, which indicated that the number of operations required to classify a single data point using Local PCA was significantly higher than using Global PCA.

In this study, the variation of electrode positioning was implemented across different sessions, which may represent a limitation as other sources of day-to-day variability may potentially affect the results. The skin-electrode impedance and the expected range of physiological variations are examples of such sources of variability. To reduce the effect of the variations of skin-electrode impedance, the skin of the subjects' forearm was cleaned using an abrasive skin gel before starting each recording session. In addition, conductive gel was used to improve signal conductivity. The physiological variations were not taken into account when computing the results of this study. Future experiments collecting data from various electrodes locations within a single session should be conducted to minimize such effect and compare the performances of the pattern recognition systems.

The number of movements studied may be considered as another limitation of this work. We presented a pattern recognition system focused entirely on wrist movements which may limit the generalization of the presented results for pattern recognition systems including finger movements. The proposed system was designed to control a cost effective prosthetic hand (Pasluosta & Chiu, 2012; Pasluosta, Tims, & Chiu, 2009), which requires the discrimination of four different wrist movements to select three different grasping configurations and to open/close the hand. Further experiments should be conducted to include different finger movements (i.e. different prehensile postures of the hand) into the pattern recognition system. This would require the selection of new muscles such as the Extensor Pollicis Brevis located on the dorsal side of the forearm or the Flexor Digitorum Superficialis located in the anterior compartment of the forearm. These muscles are mainly responsible for the flexion and/or abduction of the fingers. The challenge for obtaining a robust pattern recognition system would potentially increase due to small changes in electrode position on these new muscles may significantly affect the performance of the classification task (Andrews, Morin, & McLean, 2009).

The results presented in this work suggested that the effect of electrode shift disturbances on the MES can potentially be generalized using wavelet features and a multiclass SVM classifier embedded in a pattern recognition system. In most cases, myoelectric pattern recognition systems are very sensitive to perturbations caused by electrode shifts as indicated by a reduction in classification accuracy. These perturbations were taken into account in the proposed system, which was able to achieve higher classification accuracy than TD features (Tkach et al., 2010) and a similar accuracy when compared to TD-AR features schemes (L. Hargrove et al., 2008). These results demonstrate the feasibility of implementing wavelet features in a myoelectric pattern recognition system.

CONCLUSION

This work studied the implementation of wavelet features extracted by MRA to diminish the effect of electrode shifts disturbances affecting the myoelectric pattern recognition systems. It was found that wavelet features were able to achieve an average classification accuracy of 88.33% when this type of disturbance is introduced in the training set. This accuracy value was comparable to the values obtained by previous works using time-domain features. Two PCA frameworks were implemented to reduce the dimension of the wavelet features and to analyze their behavior under electrode shift disturbances. The performance of these PCA frameworks did not achieve significant improvement in both classification accuracy and processing time when compared to wavelet features alone. It suggested that the myoelectric channels selected in this study were not strongly correlated; hence, there is no need for PCA. A SVM classifier created with wavelet features was able to adapt to electrode shift disturbances with relatively good accuracy after information from more than two recording sessions was incorporated to the training set.

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FIGURE 1.

Left: Seven channels were distributed over five forearm muscles in able-body subjects to record MES during isometric contractions. Right: Distribution of the seven bipolar channels over the residual forearm of a subject with congenital limb loss.

FIGURE 2.

Left: Global PCA scheme; a single matrix was used to project input instances before performing multiclass classification. Right: Local PCA scheme; the projections were performed at each node of the multiclass classifier.

FIGURE 3.

A comparison of the average classification accuracies (across able-body subjects) obtained with wavelet features extracted after 4 levels of decomposition. Wavelet features without dimensionality reduction (DWT) and with dimensionality reduction performed by Global PCA and Local PCA showed no significant differences at any M-dimension.

FIGURE 4.
Comparison of the classification accuracies for DWT, Global PCA and Local PCA features extracted from the MES of subject with congenital limb loss.

FIGURE 5.

Top: Average classification accuracy across able-body subjects when electrode shift disturbances were introduced to MES. Dimensionality reduction using both Global PCA and Local PCA did not significantly improve the performance of the classifier trained with DWT features. Bottom: Computational time required for classification. A linear trend is observed for both PCA frameworks, which corresponds to the linear increase in the amount of data.

FIGURE 6.

Top: Classification accuracy for data from subject with congenital limb loss. Wavelet features (DWT) showed higher accuracies than Global PCA and Local PCA features in four out of five sessions. Bottom: Computational time required to classify a single instance using each feature set.