EVALUATION OF CLASSIFIERS PERFORMANCE USING THE MYO ARMBAND

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ABSTRACT

To provide amputees with intuitive prosthetic control systems, surface electromyography (EMG) has shown promising results in several studies. Myo armband (MYB) is a wireless, ready-to-use technology developed by Thalmic Labs, able to record eight EMG channels with limited frequency bandwidth (<100 Hz). The aim of this study was to evaluate the performance of five classifiers in order to assess the suitability of the MYB to provide reliable accuracy in comparison to the conventional EMG systems (CONV). Eight able-bodied subjects performed nine hand gestures in a crossover acquisition design. Six time-domain features were extracted from the data to evaluate the offline classification error of five classifiers: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes (NB) and Neural Networks (NN). Friedman's test showed no significant difference between CONV and MYB with six channels (P=0.10) with mean classification error of LDA (5.82 ± 3.63% vs. 9.86 ± 8.05%), SVM (9.70 ± 6.02% vs. 11.01 ± 8.79%), KNN (8.30 ± 6.00% vs. 11.12 ± 8.94%), NB (12.48 ± 8.51% vs. 13.77 ± 9.76%) and NN (1.77 ±1.28% vs. 4.64 ± 4.25%) for CONV and MYB, respectively. Although lower classification error was obtained, no significant improvement was found between MYB using eight and six channels (P=0.16).

INTRODUCTION

Surface electromyography (EMG) is a non-invasive technique that records the electrical activity of the muscles during contraction. In the pursuit of intuitive control of multifunctional upper-limb prostheses with several degrees of freedom, numerous studies have applied pattern recognition on EMG signals to identify different movements [1-13]. In the myoelectric control framework, pattern recognition assumes that the signals generated by similar gestures, contain similar features, which are distinguishable from other movements. In the pursuit of improved performance, several studies have compared classification accuracy of various classifiers, such as Support Vector Machine (SVM) [1-5], Linear Discriminant Analysis (LDA) [1-5], K Nearest Neighbor (KNN) [1-5], Bayesian Classifier (BC) [6,7] and Neural Networks (NN) [2-6], among others.

In the recent years, Thalmic Labs has developed the Myo armband (MYB), which is a wireless wearable technology able to record surface EMG. MYB is a multisensory system that records these EMG signals through eight stainless steel electrodes, placed on the forearm, with a maximum sampling frequency of 200Hz. Additionally, it includes a nine-axis inertial measurement unit, haptic feedback and Bluetooth 4.0 communication [8]. Although MYB was initially intended for entertainment, its compact design and intuitiveness have expanded its application into the biomedical engineering field such as in prosthetic hand control [9], or to provide medical image hand-free navigation in a surgical room [10].

From the myoelectric control perspective, the major limitation of the MYB is its restricted maximum sampling frequency. In pattern recognition studies, sampling frequencies above 200Hz have been extensively used [2-5,7] to capture the entire EMG frequency band. Li et al. [11], studied the relationship between sampling frequency and classification accuracy in EMG pattern recognition. Eleven hand motions were sampled at 1 kHz and downsampled up to 100Hz with a 20Hz decrease. Results indicated that classification accuracy decreases with decreased sampling, especially for sampling frequencies below 400Hz.

Therefore, the aim of this study was to evaluate the performance of five classifiers to determine the suitability of MYB for myoelectric control, despite its narrow EMG signal bandwidth (<100Hz). For this purpose, MYB was compared to a full bandwidth EMG acquisition system (CONV) in a crossover study design.

MATERIALS AND METHODS

Data Acquisition

EMG signals were recorded following a crossover study design using both acquisition systems, from eight abled-body subjects (five females/ three males, ages: 19-25 yrs.). The ethical committee of North Jutland approved the experiment. Despite the randomized system order for each subject

a) b) c) d) e) f) g) h) i)

Figure 1: Recorded hand movements a) Open hand, b) Closed hand, c) Wrist extension, d) Wrist flexion, e) Pronation, f) Supination, g) Key grip, h) Pinch and i) Rest.

acquisition, the MYB was placed first at 2cm distal to the elbow, to mark the location of six CONV (disposable Ag/AgCl bipolar electrodes) channels. CONV signals were recorded using a custom software at 2kHz sampling frequency and analogically filtered between 10-500Hz. On the other hand, MYB data was sampled at 200Hz. An acquisition software developed in MATLAB using Myo SDK MATLAB Mex Wrapper toolbox [12] was used to record the signals sent via Bluetooth 4.0.

Nine gestures (see Figure 1) of 4s duration, were recorded form each subject in randomized order. Each subject repeated the set five times. To avoid fatigue, subjects had 15s breaks between movements and three minutes' pause between sets.

Data Processing

Due to the difference in the channel number, only six MYB channels (MYB6) were considered for the comparison with CONV. In addition, the same processing steps were also applied to the eight-channel configuration (MYB8) to evaluate the possible classification improvement. We focused only on EMG sensors.

From the 4s movement recordings, only the middle 3s of the contraction were analyzed, to focus on the region with constant contraction force – steady state. [13-15]

The obtained signals were segmented using an overlapping window of 200ms with 50ms increment. Six time domain features [16,17] were extracted from these segments: waveform Length (WL), Mean Absolute Value (MAV), Willison Amplitude (WAMP), Cardinality (CARD), Slope Sign Changes (SSC) and Zero Crossings (ZC). The formulation of the last four features implies a threshold optimization to build a robust feature space. Preliminary work suggests that a threshold of 0.1:1 times the root mean square of the rest signal is required for CARD and WAMP. However, according to [18], no threshold is required for ZC and SSC. Hence, in this study the root mean square of the rest signal was only applied as threshold for CARD and WAMP. Principal component analysis was used to reduce the resulting feature space, preserving 95% of the variance.

Finally, five supervised classifiers were tested: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes (NB) and Neural Networks (NN). The number of neighbors and hidden neurons in KNN and NN were optimized resulting in 1 neighbor and 13 hidden neurons for CONV, 13 neighbors and 14 hidden neurons for MYB6 and 15 neighbors and hidden neurons for MYB8.

To maximized the amount of training data a five-fold validation procedure was applied to test the classifiers with a 4:1 training-testing ratio. Each classifier performance was evaluated based on the misclassification ratio (error).

A part from classification, the histogram of MAV, WL, ZC and SSC from both acquisition systems was computed to evaluate the effect of the different sampling frequencies. For this purpose, histograms were averaged among subjects and normalized for visibility.

Statistics

Non-parametric Friedman's pair test was employed to evaluate the difference between CONV and MYB6, as well as MYB6 and MYB8, using all classifiers. In addition, non-parametric Kruskal-Wallis test was used to compare the two best classifiers within each acquisition system. P-values less than 0.05 were considered significant for both tests.

RESULTS

Table 1 shows the mean percentage classification error and the standard deviation for LDA, SVM, KNN, NB and NN for the three acquisition systems: CONV, MYB6 and MYB8.

Friedman's pair test revealed no significantly different classification performance between CONV and MYB6 (P=0.10). On average, MYB8 showed 1.53 points less than MYB6 in the mean percentage classification error for all classifiers. Nevertheless, this difference did not imply a significant improvement (P=0.16)

NN outperformed all classifiers independently of the acquisition system. When comparing NN with the second best (LDA), NN's performance was significantly better than LDA's in CONV (P=0.02) but not in MYB6 (P=0.17) nor MYB8 (P=0.11).

Table 1: Mean classification error percentage ± standard deviation of CONV, MYB6 and MYB8

	CONV	MYB6	MYB8
LDA	5.82 ± 3.63	9.86 ± 8.05	8.33 ± 6.80
SVM	9.70 ± 6.02	11.01 ± 8.79	9.57 ± 7.63
KNN	8.30 ± 6.00	11.12 ± 8.94	9.61 ± 7.62
NB	12.48 ± 8.51	13.77 ± 9.76	11.95 ± 9.00
NN	1.77 ±1.28	4.64 ± 4.25	3.31 ± 3.37

Figure 2 depicts the computed histograms of the normalized features MAV, WL, ZC and SSC for MYB6 and CONV. Results show a wider and more evenly distributed dynamic range of MAV and WL for MYB6 than for CONV. In contrast, the distribution of ZC and SSC in CONV provides more information than MYB6.

DISCUSSION

Although the application of MYB in advanced myoelectric control is gaining interest in the research community, few studies have been carried out to evaluate its performance. Most of them, are application-oriented [9,10] and do not assess the real capabilities of MYB as an EMG acquisition system, and its potential in pattern recognition. Therefore, the objective of this study was to evaluate the suitability of MYB for hand gesture classification, and compare the effect of its narrow bandwidth with a full bandwidth acquisition systems (CONV).

The first difference between CONV and MYB can be found in the histograms of the features. MYB seems to have a broader range in MAV and WL, which provide information about the amplitude of the EMG signal. However, in the frequency-related features (SSC and ZC), MYB shows a limited dynamic range when compared to CONV. This difference in the frequency information is consistent with MYB's lower sampling frequency. In addition, the non-similar feature distributions may explain the difference in the optimal number of KNN's neighbors: 13 or 15 for MYB (depending on the number of channels), in contrast with the one required for CONV.

The obtained drop in the classification error for LDA and NN using CONV and MYB, is consistent with Li et al. [11] findings. From 1 kHz to 200Hz an approximately 3.5 percentage points drop in the average classification accuracy was found for LDA in able-bodied subjects. However, the classification error of NN and LDA, was found to be lower than in other studies such as Ortiz-Catalan [19]. Using a similar setup, classifying eleven hand motions, sampled at 2 kHz and extracting four time domain features (MAV, ZC, SSC and WL), the obtained classification errors for LDA and NN were 7.9% and 8.8%, respectively.

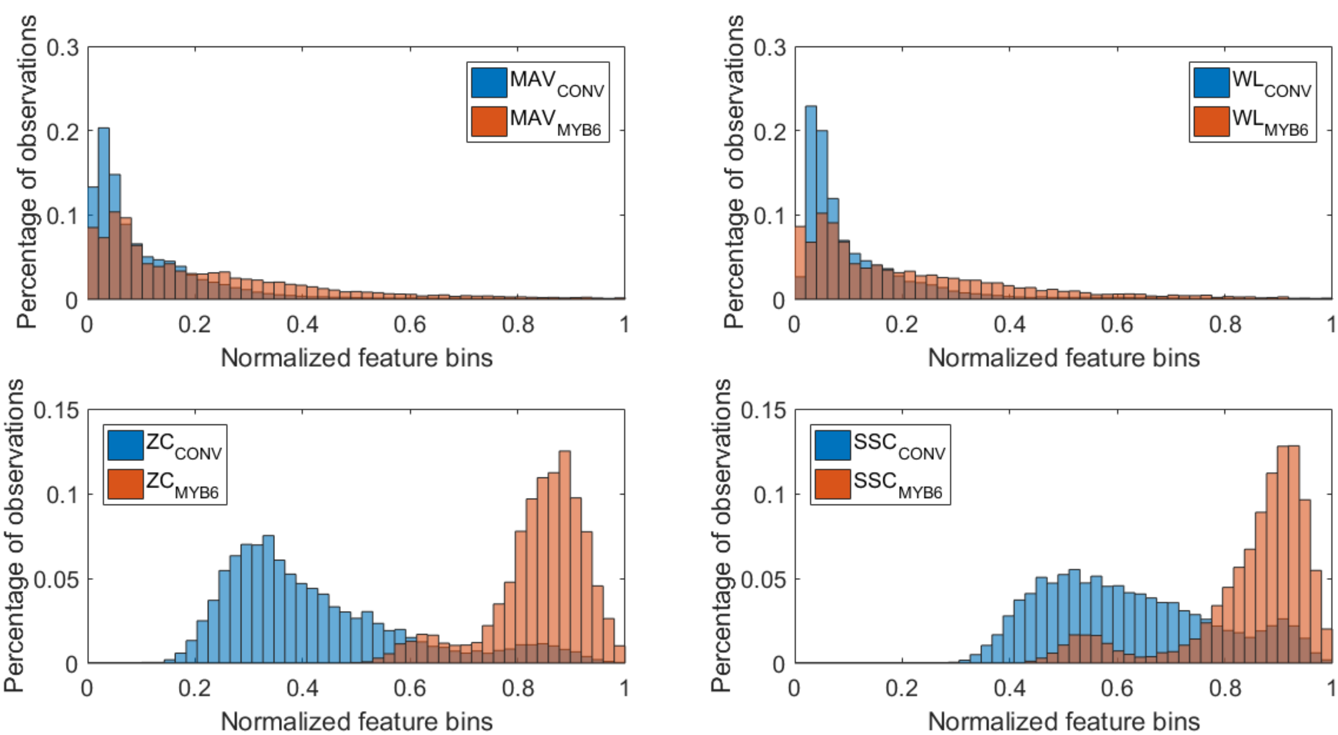

Figure 2: Normalized histograms of the normalized features MAV, WL, ZC and SSC for CONV and MYB6.

Finally, variability in the accuracy due to differences in the number of channels may not be remarkable, as the comparison of MYB6 and MYB8 showed no significant difference, despite the increase in number of channels. This was found to be supported by [20, 21] where increasing the number of channels by two, yielded in little change in accuracy.

CONCLUSION

Offline classification error of MYB and its not significant difference with CONV, demonstrated that MYB is suitable to be used as an EMG acquisition system for pattern recognition applications. Future work should focus on assessing the performance of MYB in an online configuration, and compare it to the CONV standard.

Since the MYB is an intuitive wearable (wireless, with fixed distance between electrodes and no preparation of skin), it could make the acquisition process of EMG data less time consuming and thus, more attractive for upper-limb prosthesis control systems.

REFERENCES

[1] Chen, X., & Wang, Z. J. (2013). Pattern recognition of number gestures based on a wireless surface EMG system. *Biomedical Signal Processing and Control, 8*(2), 184-192.

[2] Radmand, A., Scheme, E., Kyberd, P., & Englehart, K. (2013). Investigation of optimum pattern recognition methods for robust myoelectric control during dynamic limb movement. *Evaluation, 1500*, 12.

[3] Kamavuako, E. N., Rosenvang, J. C., Horup, R., Jensen, W., Farina, D., & Englehart, K. B. (2013). Surface versus untargeted intramuscular EMG based classification of simultaneous and dynamically changing movements. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21*(6), 992-998.

[4] Riillo, F. (2014). Optimization of EMG-based hand gesture recognition: Supervised vs. unsupervised data preprocessing on healthy subjects and transradial amputees. *Biomedical Signal Processing and Control, 14*, 117-117-.

[5] Al Omari, F., Hui, J., Mei, C., & Liu, G. (2014). Pattern recognition of eight hand motions using feature extraction of forearm EMG signal. *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences, 84*(3), 473-473-480.

[6] U. Sahin, & F. Sahin. (2012). Pattern recognition with surface EMG signal based wavelet transformation. *2012 IEEE International Conference on Systems, Man, and Cybernetics (SMC),* pp. 295-300.

[7] X. Chen, A. Ke, X. Ma, & J. He. (2016). SoC-based architecture for robotic prosthetics control using surface electromyography. *2016 8th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), 01.* pp. 134-137.

[8] Thalmic Labs. TechSpecs | myo battery life, dimensions, compatibility and more.

[9] Johns Hopkins University Applied Physics Laboratory (APL). APL's modular prosthetic limb reaches new levels of operability.

[10] Decleir, E. (2016,). Using myo during surgery with ADORA assistant™.

[11] Li, G., Li, Y., Yu, L., & Geng, Y. (2011). Conditioning and sampling issues of EMG signals in motion recognition of multifunctional myoelectric prostheses. *Annals of Biomedical Engineering, 39*(6), 1779-1787.

[12] Tomaszewski, M. (2016). Myo SDK MATLAB MEX wrapper

[13] Englehart, K., Englehart, K., Hudgins, B., & Parker, P. A. (2000). Time-frequency based classification of the myoelectric signal: Static vs. dynamic contractions. *Time-Frequency Based Classification of the Myoelectric Signal: Static Vs. Dynamic Contractions, 1.* pp. 317-320.

[14] Englehart, K., Hudgins, B., & Parker, P. A. (2001). A wavelet-based continuous classification scheme for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, 48*(3), 302-311.

[15] Pla Mobarak, M., Mobarak, M. P., Mobarak, M. P., Guerrero, R. M., Gutierrez-Salgado, J. M., & Dorr, V. L. (2014). Hand movement classification using transient state analysis of surface multichannel EMG signal. *Hand Movement Classification using Transient State Analysis of Surface Multichannel EMG Signal,* pp. 1-6.

[16] Ortiz-Catalan, M. (2015). Cardinality as a highly descriptive feature in myoelectric pattern recognition for decoding motor volition. *Frontiers in Neuroscience, 9*

[17] Phinyomark, A., Phukpattaranont, P., & Limsakul, C. (2012). Feature reduction and selection for EMG signal classification. *Expert Systems with Applications, 39*(8), 7420-7420-7431.

[18] Kamavuako, E. N., Scheme, E. J., & Englehart, K. B. (2016). Determination of optimum threshold values for EMG time domain features; a multi-dataset investigation. *Journal of Neural Engineering, 13*(4), 046011-10.

[19] Ortiz-Catalan, M., Brånemark, R., & Håkansson, B. (2013). BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms. (research). *Source Code for Biology and Medicine, 8*(1), 11-11-.

[20] Li, G., Schultz, A. E., & Kuiken, T. A. (2010). Quantifying pattern Recognition—Based myoelectric control of multifunctional transradial prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 18*(2), 185-185-192.

[21] Scheme, E., & Englehart, K. (2014). On the robustness of EMG features for pattern recognition based myoelectric control; a multi-dataset comparison. *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* pp. 650-653.