35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Improving Transient State Myoelectric Signal Recognition in Hand Movement Classification using Gyroscopes

Alexander Boschmann[1], Barbara Nofen[2] and Marco Platzner[3]

***Abstract*— Pattern recognition of myoelectric signals in upper-limb prosthesis control has been subject to intense research for several years. However, few systems have yet been successfully clinically implemented. One possible explanation for this discrepancy is that published reports mostly focus on classification accuracy of myoelectric signals recorded under laboratory conditions as the metric for the system's performance. These data are usually acquired only during the static state of the contraction in a fixed seated position. This supports the test subject in performing repeatable contractions throughout the experiment and generally results in an unrealistically high classification accuracy. In clinical testing however, subjects have to perform various activities of daily living, causing the limb to move in different positions. These variations in limb positions can significantly decrease robustness and usability of myoelectric control systems. Recent reports have shown that the so-called limb position effect can be resolved for the static state of the signal by adding accelerometer data to the feature vector. Including data from the transient state of the signals for classifier training generally significantly increases the classification error so it is mostly not considered in published reports. In this paper, we investigate the classification accuracy of transient EMG data, taking into account the limb position effect. We demonstrate that a classifier trained with features from EMG, accelerometer and gyroscope outperforms classifiers using only EMG or EMG and accelerometer data when classifying transient EMG data.**

I. Introduction

Myoelectric signals have been used in upper-limb prostheses control schemes for more than 30 years [1]. Conventional control schemes based on amplitude [2] or rate of change [3] of the recorded signals can proportionally operate one degree of freedom. Switching between different prosthetic functions is usually achieved by using co-contractions [4].

One approach towards an intuitive and user friendly control scheme for upper-limb myoelectric prostheses is pattern recognition. Pattern recognition based control schemes are an active research area and can potentially enable the amputee to intuitively operate multiple degrees of freedom [5]. They are based on the assumption that a set of features extracted from electromyographic (EMG) signals is repeatable for a specific movement. The signal processing chain can be broken down to three components: the feature extraction, the dimensionality reduction and the pattern classification. During the first two steps attributes are extracted from myoelectric signals (MES) and reduced by selecting features for more robust and accurate classification. In the last step pattern matching algorithms are applied to detect the class of the input data [6]. Various feature extraction and classification algorithms have been tested for upper-limb prosthesis control and achieved high classification accuracies under laboratory conditions [7]–[12].

However, there are disparities between experimental performance and actual clinical results. One challenging factor in pattern recognition based control schemes is operating the prosthesis in various limb positions. Scheme et al. [16] showed that variations in limb positions used in the training phase of the classifier can have a significant impact on classification accuracy and robustness of the system. In their work they demonstrated that a combined system of EMG and accelerometer sensor data outperformed a EMG only system in classifying 8 hand and wrist movements acquired in 8 different limb positions. A similar approach was presented by Chen et al. [18].

Fougner et al. [13], [15] proposed training the classifier in all possible positions and measuring the limb orientation with accelerometers. In that study, 8 hand and wrist movements recorded in 5 different locations were used. Additionally to training in a single and multiple limb positions they investigated a two-stage position aware classifier where the limb position was first detected by a classifier based on accelerometer data, followed by a position specific motion classifier. This approach is tedious, as it requires the user to perform training sets in each position. Another method presented is a single-stage position aware classifier where EMG time domain features and features from the accelerometer data were concatenated into one feature vector. The average classification error could be decreased from 18% to 5%.

Most published reports including the aforementioned investigating pattern recognition based myoelectric control schemes in the context of the limb position effect only use the static state of the EMG signal for classification. An EMG signal representing a hand movement can be separated into a short, approximately 1 s long transient state followed by the static state of the contraction. Including signals from the transient state into a static state based classification problem generally results in an increase in classification error. Hargrove et al. [14] investigated the usability of a pattern-recognition based myoelectric control system using a virtual clothespin test. The test involved repositioning a clothespin in a virtual environment between two bars and counting the number of pins successfully placed in a set of time or timing how long it takes to place a given number of pins. As a result

[1]Alexander Boschmann is with the Department of Computer Science, University of Paderborn, 33098 Paderborn, Germany (e-mail: alexander.boschmann@upb.de).

[2]Barbara Nofen is with the Department of Computer Science, University of Paderborn, 33098 Paderborn, Germany (e-mail: bnofen@mail.upb.de).

[2]Marco Platzner is with the Department of Computer Science, University of Paderborn, 33098 Paderborn, Germany (e-mail: platzner@upb.de).

978-1-4577-0216-7/13/$26.00 ©2013 IEEE

it was shown that adding transient state data along with static state data to the classification problem, the average pin placement time improved while the classification error increased simultaneously.

In this paper we investigate the problem to classify the transient state EMG signal in an experiment distinguishing 8 hand and wrist movements performed in 5 different limb positions. First we use the accelerometer based method presented by Fougner and Scheme [13] to classify the transient state signal and compare the result to using EMG signals only. Then we introduce a hybrid classifier using EMG, accelerometer and gyroscope data. We demonstrate that it outperforms the EMG and accelerometer based method.

The paper is structured as follows. The setup of the EMG and inertia measurement unit (IMU) sensor system and the conducted experiment, as well as the signal processing and feature extraction are presented in Section 2. The experiments are evaluated in Section 3. Finally, Section 4 concludes the paper.

II. Experiment

A. Methods

To investigate transient state classification problem in context with the limb position effect, an experiment was conducted. EMG, accelerometer and gyroscope data corresponding to 8 hand and wrist motions were acquired from two healthy normally limbed subjects (25 year old female, 26 year old male).

The EMG data were collected by a BioVision NeXus 16 [19] at 1024 Hz from four Ag/Cl electrode pairs on the forearm. Each electrode had a diameter of 1 cm and the center to center distance between adjacent electrodes was about 1 cm. A reference electrode was placed on the elbow. Accelerometer and gyroscope data were acquired by a CH Robotics UM6 IMU [20] above the wrist of the subjects. Fig. 1 illustrates the experimental setup. The experiment consisted of four runs, each consisting of performing a sequential set of hand movements in 5 different limb positions illustrated in Fig. 2. The test subject was prompted to perform the following sequence of movements: wrist flexion (m1), wrist extension (m2), pronation (m3), supination (m4), hand open (m5), lateral grip (m6), pincer grip (m7) and relax (m8). Each movement was held for 5 seconds, followed by a 5 seconds pause. The movement can be subdivided into a approximately 1 s transient state and a 4 s static state of which the first 3 s were used for classification. This is depicted in Fig. 4. The acquired EMG, accelerometer and gyroscope data were grouped by limb position and equally subdivided into a training data and a test data part.

B. Signal Processing

The data were segmented using a 250 ms sliding window with 50 ms increment for feature extraction. Five time domain features (mean average value, wave length, zero crossings, sign slope change, autoregressive feature) were extracted from the EMG signal. Two time domain features (mean average value, wave length) were extracted from the accelerometer signal and two time domain features (mean average value, root mean square) from the gyroscope data. The raw data from one position (P2) is illustrated in Fig. 3. As classifier we use support vector machines which have been successfully used for EMG signal classification [17].

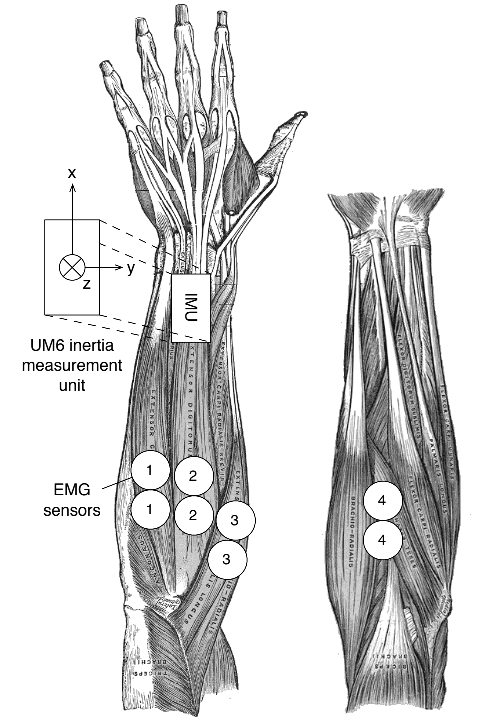

Fig. 1. Experimental setup showing placement of the EMG electrode pairs and the location and orientation of the IMU. EMG signals were acquired from (1) M. extensor capri ulnaris, (2) M. extensor digitorum communis, (3) M. extensor capri radialis and (4) M. brachio radialis.

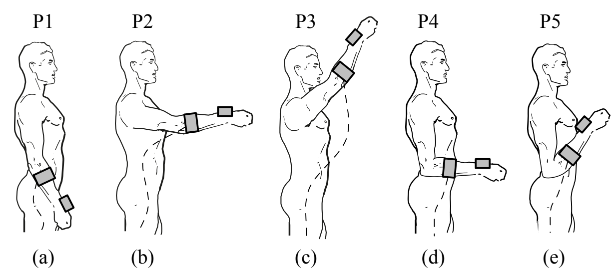

Fig. 2. The experiment data were acquired in following limb positions. P1: Straight arm hanging down (a), P2: straight arm reaching forward (b), P3: straight arm reaching up 45° (c), P4: humerus hanging at side, forearm reaching forward 90° (d), P5: humerus hanging at side, forearm reaching up 45° (e). Illustration is based on [15].

III. Results

A. Training in one position

First, we investigate the performance if the classifier is only trained in one position and tested with the data of the other positions. Therefore we create 4 groups of classifiers: one only using EMG data (EMG), one using EMG and accelerometer (EMG+ACC), one using EMG and gyroscopes (EMG+GYR) and one using a combination of EMG, accelerometer and gyroscopes (EMG+ACC+GYR).

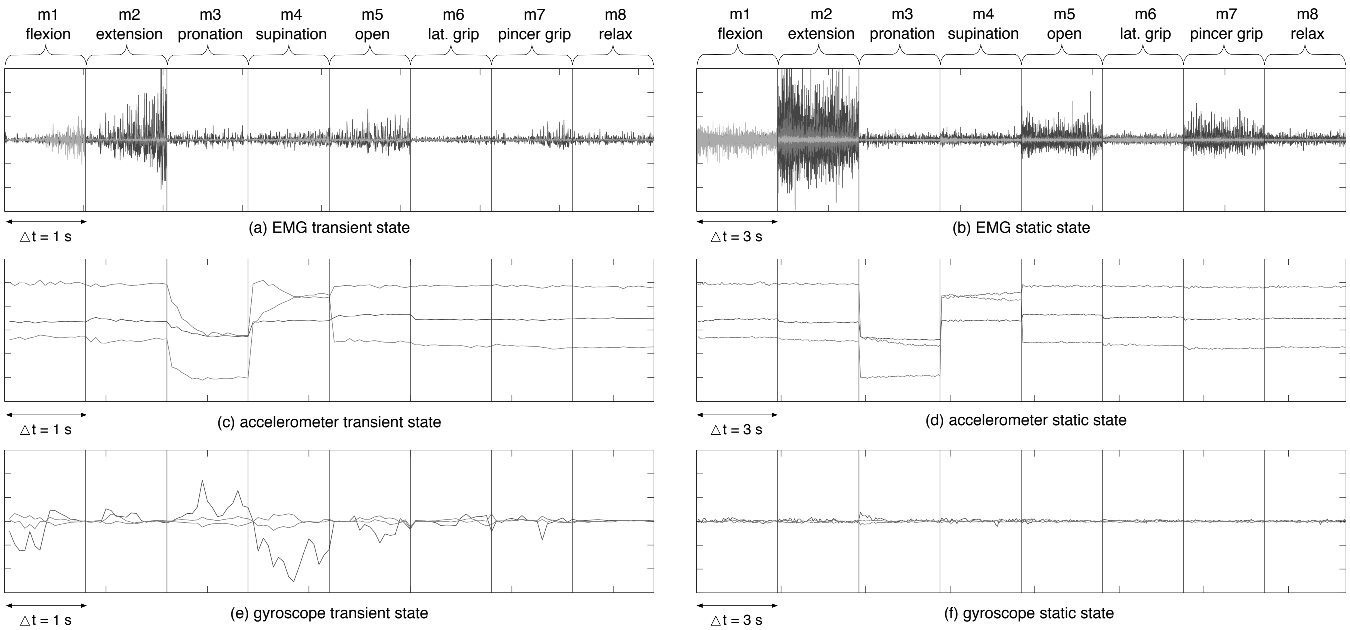

Fig. 3. Sample raw data of EMG (a)-(b), accelerometer (c)-(d), and gyroscope (e)-(f) corresponding to the 8 movements in position P2 are displayed. The transient state is illustrated on the left, the static state of the movement on the right side of the figure. The time is depicted in the X-axis. In (c) and (d), the Y-Axis indicates linear acceleration $[m/s^2]$, while in (e) and (f) the Y-Axis indicates angular velocity $[°/s]$.

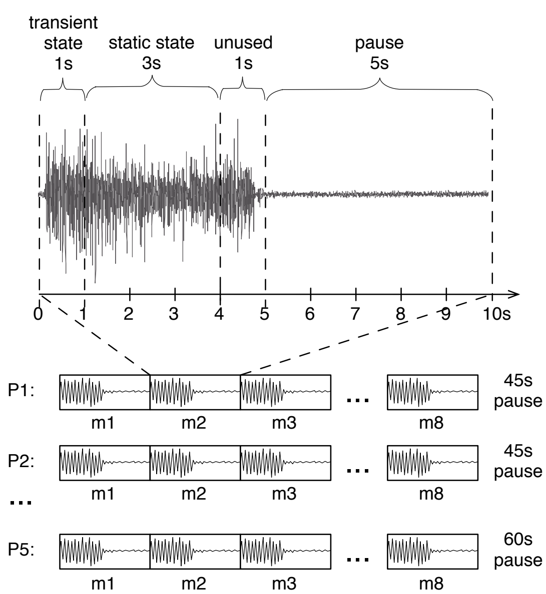

Fig. 4. The EMG signal of one contraction is displayed. It consists of 1 s transient and 4 s static state of which the first 3 s were used, followed by 5 s pause. Below one set of the experimental protocol consisting of 5 positions with 8 movements each is illustrated.

We also create 5 groups of training and test data: training transient state, testing transient state (TR-TR), training static state, testing static state (ST-ST), training transient and static state, testing transient state (TRST-TR), training transient and static state, testing static state (TRST-ST) and training transient and static state, testing transient and static state (TRST-TRST). The results are illustrated in Fig. 5. The values displayed are averaged mean intra- and inter-position errors. In the first column we see a high classification error

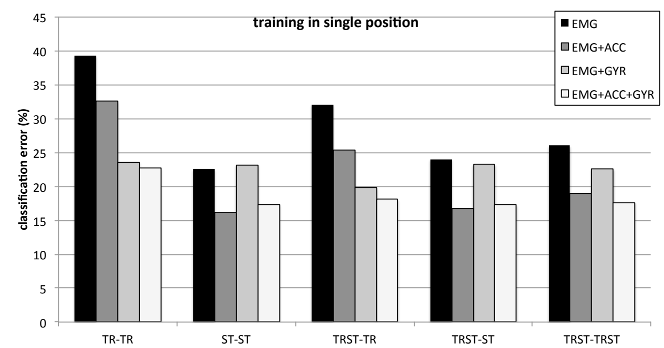

Fig. 5. Results of the 'Training in one position' experiment. The classification error is shown on the y-axis.

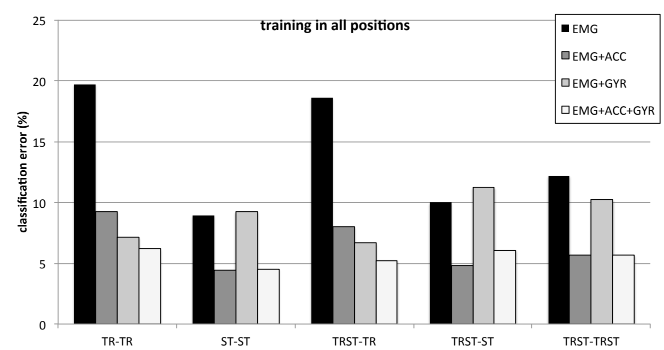

Fig. 6. Results of the 'Training in all positions' experiment. The classification error is shown on the y-axis.

of all classifiers due to the combination of limb position effect and the problem of transient state classification. EMG alone shows the greatest difficulty to correctly classify the transient state. EMG+GYR and EMG+ACC+GYR clearly outperform EMG and EMG+ACC. A possible explanation of the superiority of gyroscope data to accelerometer data can be concluded from the raw data in Fig. 3 where the gyroscope raw data shows a higher diversity than the accelerometer data in the transient state.

ST-ST is dominated by EMG+ACC and EMG+ACC+GYR, indicating that accelerometer data contains more useful information about the static state than gyroscope data. In general, setups where the transient state is tested are dominated by EMG+ACC and EMG+ACC+GYR while setups where the static state is classified are dominated by EMG+GYR and EMG+ACC+GYR.

B. Training in all positions

In this section the classifiers use training data from all limb positions. The results of this experiment are shown in Fig. 6. The same classifier and training and test datasets as in the previous experiment are used. It is noticeable that all classification errors are significantly decreased compared to training in one position.

As in the previous experiment EMG alone performs worst when testing the transient state while EMG+GYR and EMG+ACC+GYR perform best. The setups testing data from the static state are again dominated by EMG+ACC and EMG+ACC+GYR. When testing data from the static state EMG+GYR shows about the same classification error as EMG. This can also be directly concluded from the raw data where it is evident that in the static state no additional information is gained by the gyroscopes.

In both experiments the hybrid classifier consisting of EMG, accelerometer and gyroscope data (EMG+ACC+GYR) shows about the same as or better results than EMG+ACC when testing the static state of the movement. When testing the transient state, it EMG+ACC+GYR outperforms EMG+ACC by 15%-45%.

IV. Discussion

The results suggest that it can be beneficial to use gyroscopes as an additional input to EMG and accelerometer data. Like accelerometers, gyroscopes are small, relatively cheap and easily integrated into a prosthesis socket. Both inertia sensors do not provide an estimation of muscle force, but the results suggest that both can provide additional information as classification input in a EMG pattern recognition system. Although the experiment presented in this paper is more realistic than many experiments from previous reports, they are still performed in a laboratory setup. As such, we are planning to repeat the experiment in a virtual environment and using usability oriented metrices as an estimation for the system's performance. Also, gyroscope can probably provide useful information about dynamic and simultaneous movements which we will also investigate.

References

[1] P. Herberts, C. Almstrom, R. Kadefors, and P. Lawrence, "Hand Prosthesis Control Via Myoelectric Patterns.", Acta. Orthop. Scand., 8(1):389-409, 1973.

[2] D. Childress, "A myoelectric three state controller using rate sensitvity", Proc. 8th Int. Conf. Math. Biol. and Ecology (ICMBE), 1969.

[3] D. S. Dorcas and R. N. Scott, "A three-state myo-electric control", Med. Biol. Eng. Comp., 4(4):367-370, 1966.

[4] C. Lake and J. M. Miguelez, "Evolution of microprocessor based control systems in upper extremity prosthetics", Technol. Disabil., 15(2):63-71, 2003.

[5] P. A. Parker, K. B. Englehart, and B. S. Hudgins, "Myoelectric signal processing for control of powered limb prostheses", J. Electromyogr. Kinesiol., 16(6):541-548, 2006.

[6] P. Kaufmann, K. B. Englehart, and M. Platzner, "Fluctuating EMG Signals: Investigating Long-Term Effects of Pattern Matching Algorithms", Proc. 32nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), pp. 6357-6360, Sept. 2010.

[7] K. B. Englehart, B. S. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations", Med. Eng. Phys., 21(6-7):431-438, Nov. 1999.

[8] D. Graupe, J. Salahi, and K. H. Kohn, "Multifunctional prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals", J. Biomed. Eng., 4(1):17-22, Jan. 1982.

[9] Y. Huang, K. B. Englehart, B. S. Hudgins, and A. D. C. Chan, "A Gaussian Mixture Model Based Classification Scheme for Myoelectric Control of Powered Upper Limb Prostheses", IEEE Trans. Biomed. Eng., 52(11):1801-1811, Nov. 2005.

[10] L. J. Hargrove, E. J. Scheme, K. B. Englehart, and B. S. Hudgins, "Multiple Binary Classifications via Linear Discriminant Analysis for Improved Controllability of a Powered Prosthesis", IEEE Trans. Neural Syst. Rehabil. Eng., 18(1):49-57, Feb. 2010.

[11] K. B. Englehart, B. S. Hudgins, and P. A. Parker, "A Wavelet-Based Continuous Classification Scheme for Multifunction Myoelectric Control", IEEE Trans. Biomed. Eng., 48(3):302-311, Mar. 2001.

[12] A. D. C. Chan and K. B. Englehart, "Continuous Classification of Myoelectric Signals for Powered Prostheses using Gaussian Mixture Models", Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), pp. 2841-2844, Sept. 2003.

[13] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and O. Stavdahl, "Resolving the Limb Position Effect in Myoelectric Pattern Recognition", IEEE Trans. Neural Syst. Rehabil. Eng.

[14] L. Hargrove, Y. Losier, B. Lock, K. Englehart and B. Hudgins, "A Real-Time Pattern Recognition Based Myoelectric Control Usability Study Implemented in a Virtual Environment", Proc. 29h Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), 2007.

[15] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and O. Stavdahl, "A Multi-Modal Approach for Hand Motion Classification Using Surface EMG and Accelerometers", Proc. IEEE Eng. Med. Biol. Soc., 2011.

[16] E. Scheme, A. Fougner, O. Stavdahl, A. D. C. Chan, and K. Englehart, "Examining the Adverse Effects of Limb Position on Pattern Recognition Based Myoelectric Control", Proc. IEEE Eng. Med. Biol. Soc., 2010.

[17] A. Boschmann and M. Platzner, "Reducing Classification Accuracy Degradation of Pattern Recognition Based Myoelectric Control caused by Electrode Shift using a High Density Electrode Array", Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), 2012.

[18] Liang Chen, Yanjuan Geng, Guanglin Li, "Effect of upper-limb positions on motion pattern recognition using electromyography", Proc. IEEE 4th Int. Congress on Image and Signal Proc., pp.139-142, 15-17 Oct. 2011.

[19] Mind Media B.V., "The Nexus System", Available: $http://www.mindmedia.nl/CMS/en/products/nexus-systems.html$

[20] CH Robotics LLC., "UM6 Orientation Sensor", Available: $http://www.chrobotics.com/shop/orientation-sensor-um6.html$