Proceedings Paper:
Azab, A.M., Arvaneh, M. and Mihaylova, L.S. (2017) Estimation of Joint Angle Based on Surface Electromyogram Signals Recorded at Different Load Levels. In: 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Societ, 11/07/2017-15/07/2017, Seogwipo, South Korea. Institute of Electrical and Electronics Engineers, pp. 2538-2541. ISSN: 1557-170X.

https://doi.org/10.1109/EMBC.2017.8037374

Estimation of Joint Angle Based on Surface Electromyogram Signals Recorded at Different Load Levels

Ahmed M. Azab[1], Mahanz Arvanch[2], and Lyudmila S. Mihaylova[3]

Abstract— **To control upper-limb exoskeletons and prostheses, surface electromyogram (sEMG) is widely used for estimation of joint angles. However, the variations in the load carried by the user can substantially change the recorded sEMG and consequently degrade the accuracy of joint angle estimation. In this paper, we aim to deal with this problem by training classification models using a pool of sEMG data recorded from all different loads. The classification models are trained as either subject-specific or subject-independent, and their results are compared with the performance of classification models that have information about the carried load. To evaluate the proposed system, the sEMG signals are recorded during elbow flexion and extension from three participants at four different loads (i.e. 1, 2, 4 and 6 Kg) and six different angles (i.e. 0, 30 , 60, 90, 120, 150 degrees). The results show while the loads were assumed unknown and the applied training data was relatively small, the proposed joint angle estimation model performed significantly above the chance level in both the subject-specific and subject-independent models. However, transferring from known to unknown load in the subject-specific classifiers leads to 20% to 32% loss in the average accuracy.**

I. INTRODUCTION

Upper-limb motion is essential for most daily human activities, such as eating, drinking, and washing face, etc. Many research studies are now focusing on how to assist people who are disabled or elderly via the development of power-assist robotic systems to support these daily functions [1]–[3]. It has been widely presented that power-assist robotic systems can be operated using surface electromyogram (sEMG [4] which reflects electrical activities of muscles [5]. The sEMG signals of muscles can be used as input information for controlling exoskeleton robots [6]. However, most of the systems introduced so far are expensive and not mature enough to be used out of laboratories.

One of control signals required to operate a power-assisted robotic system can be obtained by estimating the joint angle based on the obtained sEMG [7]. Several studies propose mathematical models to estimate joint angles [8], [9]. For example, Aung et al estimate the angle of shoulder based on sEMG signals to control a virtual reality (VR) human model [9]. However, most of these studies do not consider load variations, which can significantly affect the accuracy of joint angle estimation. Indeed [10] shows that changes of the load level dropped the accuracy of myoelectric control system up to %60. Nevertheless, there are only few research studies focusing on reducing the error in estimating joint angle caused by load variations. For example, [10], [11] combine information extracted from accelerometer with sEMG and achieved 5-10% improvement in the accuracy of joint estimation. Furthermore, there is a study that used force measurements with sEMG [12] and this study showed that the average error could be reduced from 20.44% to 8.48% [12].

This paper focuses on joint angle estimation using sEMG signals when the load carried by the user is unknown. To reduce the impact of load variations on the join angle estimation accuracy, we propose to pool sEMG data from different loads and use the pooled data for training the classification models. Thus, using training data pooled from different loads would enable the model to learn effects of the load variations on the sEMG data. Two different classification models are proposed under three different conditions, namely 1) a subject-specific model with known load, 2) a subject-specific model with unknown load, and 3) a subject-independent model with unknown load. We compare the results of these models and discuss if using pooled sEMG data recorded from different loads as training data can lead to an accurate estimation of the joint angle.

To develop a reliable system that is commercially inexpensive and usable in mobile systems with limited computational capacities, we use a cheap EMG acquisition system along with machine learning algorithms that are computationally inexpensive. Thus, the proposed system can be potentially used as a key step in developing a complete controller for the upper-limb power-assist robotic systems. To evaluate the proposed system, the sEMG signals from the biceps muscle during elbow flexion and extension are recorded from three participants at different loads (1, 2, 4, 6 kg) and angles (0°, 30°, 60°, 90°, 120°, 150°).

The remainder of this paper is organized as follows. Section II describes the proposed method. The performed experiments are explained in Section III. Section IV presents the experimental results, and finally Section V concludes this paper

II. METHODOLOGY

A. Preprocessing

The output of the EMG sensor is not a raw EMG signal but rather an amplified (10053x), rectified, and smoothed signal. Disjoint segmentation with a window of 300 ms width is applied to enhance signal stationarity [13].

[1]Ahmed.m.Azab is a PhD student at Automatic control and system Engineering Department, University of Sheffield , Sheffield, United Kingdom ammazab1@sheffield.ac.uk

[2]Mahanz Arvanch Lecturer at Automatic control and system Engineering Department, University of Sheffield , Sheffield, United Kingdom m.arvaneh@sheffield.ac.uk

[3]Lyudmila S Mihaylova Professor at Automatic control and system Engineering Department, University of Sheffield , Sheffield, United Kingdom b.d.researcher@ieee.org

B. Feature extraction and classifications

Two time domain features are calculated, namely the Standard Deviation (STD) and the Root Mean Square (RMS) of the EMG signals which are two of the most commonly used time domain features in EMG studies [14]. The STD and RMS features of an EMG window are calculated as below:

$$STD = \sqrt{\frac{1}{N}\sum_{i=0}^{n}(X_i - \bar{X})^2}, \tag{1}$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=0}^{N}X_i^2}, \tag{2}$$

where x denotes the EMG voltage at the i^{th} sample, N is the total number of sample points, and $\bar{X}$ is the mean of the considered EMG interval.

Two classification techniques, namely k-Nearest Neighbours algorithm (KNN) and Naive Bayes classifiers (NB) [15], are applied on the extracted EMG features to identify the corresponding joint angle. KNN identifies the class of a new instance query based on majority of K-Nearest Neighbour instances available in train data. NB classifier is a probabilistic technique where uses Bayes' rules to calculate the probability of classes.

As the experiment is done under six different angles (i.e. 0°, 30°, 60°, 90°, 120° and 150°), six classes are defined for classification. As mentioned before, each subject performs three complete sets of trials with a sufficient rest period between each trial to prevent fatigue. Moreover, the proposed algorithms in identifying the joint angles are validated using three-folds cross validation.

In this paper, the classifiers are trained under three different conditions.

1) Load-dependent & subject-dependent classification: The training and testing features are extracted from data with the same load and the same subject. In this condition, the three-fold cross-validation is conducted as follows: For each subject and each load, features from two trials are used as the training data and features from the remaining trial are used as the test data. Hence, the trained model is tested on the sEMG data recorded with the same load.
2) Load-independent & subject-dependent classification: In this condition, training and test data are obtained from the same subject by pooling data from the different loads together. Thus, the classifiers aim to identify the joint angle regardless of the load that the corresponding subject is carrying. In this condition, the three-fold cross-validation is conducted for each subject using all features of two trials obtained from all the loads as the training data and all features from the remaining trial as the test data.
3) Load-independent & subject-independent classification: In this condition, we aim to identify the joint angle of a new subject regardless of the load that he is carrying using a classifier trained by the data from other subjects. Thus, for three-fold cross validation, the classifier is trained using all the features from all the loads carried by two subjects. Subsequently, the classifier is tested using all the features obtained from the remaining subject.

III. EXPERIMENT

A. Participants

Three healthy male participants aged between 20-30 years old participated in this study. All of them gave their signed consents before the experiment. The experimental protocol was approved by the graduate study department for ethical clearance at Military Technical College in Egypt. Participants with any musculoskeletal diseases were excluded from this study.

B. Proposed low-cost data recording system

In this study we use our proposed low cost data recording system to record sEMG signals [16]. The proposed system performs the following steps: signal acquisition, then signal digitalization, data segmentation, after that signal processing (feature extraction and classification), and finally, control signal generation unit. A sampling frequency of 1 KHz is used to minimise hardware requirements in terms of memory, processing power and processing time (i.e. less memory size, smaller processor, and less processing time to save power).

As shown in shown in Fig. 1, the proposed low-cost data recording system consists of EMG sensor electrodes for signal acquisition, an EMG muscle sensor kit, and an Atmel ATmega640 microcontroller for signal conditioning and a Matlab program for signal processing and classification. The Atmel ATmega640 microcontroller receives the surface EMG signals to control the robotic arm and produce its motion through the servomotors. In our previous study, the proposed low-cost hardware is validated against EMG100C, the professional EMG signal module of the Biopack system, using several stages of validation, and shows that it provides the same results given by the professional Biopack system. Therefore, the proposed system reduces our target costs with acceptable accuracy [16].

C. Experiment Protocol

EMG is acquired using the proposed low-cost muscle sensor kit from three electrodes. As the standard measurement technique for angle estimation, two electrodes are placed over the biceps muscle attached to the subject's right arm. The distance between the two electrodes is 2 cm and the placement is in the direction of the muscle fibers. The third electrode is the reference electrode placed at one of the arm bones [17].

Elbow flexion and extension are performed (as shown in Fig. 2) at six angles (i.e. 0°, 30°, 60°, 90°, 120°, 150°) and at the different loads (i.e. 1, 2, 4, 6 kg). The experiments are conducted with all loads at each angle as follows. At angle 0°, each individual load is lifted by the subject under test while the sEMG signal of the biceps muscles is recorded

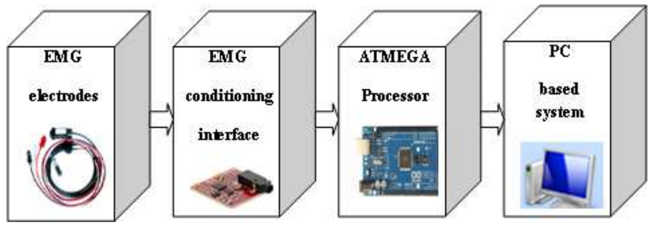

Fig. 1. Proposed low cost system

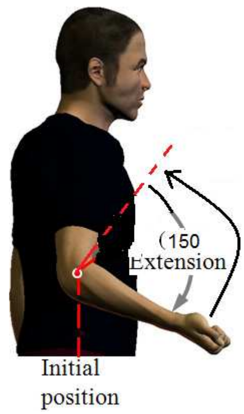

Fig. 2. Elbow flexion and extension

over 20 seconds without motion. After that, at each angle (30° to 150°), the subject moves his elbow from the zero position (angle 0° where depicted as initial position in Fig. 2) to the required angle and vice versa for 20 seconds while the sEMG signal is recorded. The participants are instructed to keep their movement at a constant speed. These sEMG signals are saved to be analysed using algorithms developed in Matlab.

IV. Results

The obtained results are divided into three groups, each refers to one of the three classification conditions.

A. Load-dependent & subject-dependent classification

Tables I and II show the average cross-validation accuracy of identifying the joint angle for each subject and each load (i.e. load-dependent & subject-dependent classification condition). Tables I and II report the results of the KNN and the NB classifiers respectively. Having 6 different angles to classify, the chance level is around 16%. When the load is known, the KNN and NB classifiers are able to identify joint angles with accuracies considerably higher than chance level. Comparing the results show that when the load is known the KNN classifier is on average more accurate than the NB classifier in identifying the joint angles (i.e. 73.15% versus 68.51%). More specifically, on average the KNN classifier outperforms the NB classifier for all subjects. In addition, on average the KNN classifier outperforms the NB classifier for the loads 1 Kg, 2 Kg, and 6 Kg.

TABLE I

Average cross-validation results in identifying the joint angles for subject-dependent KNN classifiers when load is known [accuracy%]

	Subject 1	**Subject 2**	**Subject 3**	**Mean**
1 Kg	83.33	83.33	50	72.22
2 Kg	94.44	66.67	94.44	85.18
4 Kg	77.78	66.70	33.33	59.27
6 Kg	83.33	94.44	50	75.92
Mean	84.72	77.77	56.94	73.15

TABLE II

Average cross-validation results in identifying the joint angles for subject-dependent Naive Bayesian (NB) classifiers when load is known [accuracy%]

	Subject 1	**Subject 2**	**Subject 3**	**Mean**
1 Kg	72.22	83.34	50	68.53
2 Kg	83.34	61.00	77.79	74.04
4 Kg	94.44	72.22	33.33	66.66
6 Kg	72.22	72.22	50	64.82
Mean	80.56	72.19	52.78	68.51

TABLE III

Average cross-validation results in identifying the joint angles for subject-dependent classifiers when load is unknown [accuracy%]

	Subject 1	**Subject 2**	**Subject 3**	**Mean**
KNN	57.33	53	48.67	53
NB	43.33	32	33	36.11

B. Load-independent & subject-dependent classification

The results of identification of joint angles using NB and KNN classifiers for the load-independent & subject-dependent classification condition are shown in Table III. Table III shows that the results exceed 50% accuracy for identifying the joint angle when the load is unknown using KNN classifier. Considering 16% as the chance level, the KNN and NB classifiers perform successfully higher than the chance level for all the three subjects. Furthermore, the KNN classifier outperforms the NB classifiers by an average of 16.89%. This outperformance is significant as it is observed for all the three subjects.

Comparing the results of the load-dependent & subject-dependent classification condition with load-independent & subject-dependent classification condition reveals that discarding the load information from the classification could yield significant loss in the accuracy (e.g. on average 20% in KNN and 32% in NB).

C. Load-independent & subject-independent classification

Table IV shows the results of the load-independent & subject-independent classification condition. In this part, the goal is to identify the joint angle of a new subject regardless of the load that he is carrying. Thus, the classifiers are trained using data from all the loads of the other subjects. The

TABLE IV
AVERAGE CROSS-VALIDATION RESULTS IN IDENTIFYING THE JOINT ANGLES FOR SUBJECT-INDEPENDENT CLASSIFIERS WHEN LOAD IS UNKNOWN [ACCURACY%]

	KNN	NB
Mean	24.7	36

obtained accuracies are ranged between 22% to 30% with mean of 24.7% for KNN, and 32% to 43% with mean of 36% for NB. Although all the results are above the chance level, the KNN and NB classifiers only achieve 24.7% and 36% average correct accuracies respectively. As can be seen in Table III and IV, transferring from subject dependent condition to subject independent condition, when load is unknown, result in 19% decrease in the accuracy of the KNN classifier.

V. CONCLUSIONS

This paper shows that the load variations can have a great impact on the accuracy of elbow-angle estimation. In order to estimate the joint angle, two classification techniques, KNN and NB, are applied on the extracted EMG features. Three different classification conditions are considered: 1) a subject-dependent classification when the carried load is known; 2) a subject-dependent classification when the carried load is unknown; and 3) a subject-independent classification when the carried load is unknown. Importantly, to cope with the uncertainties made by variations in the load, the classifiers in the second and third conditions are trained using sEMG data gathered from all the loads.

The proposed algorithms are evaluated using data collected from 3 subjects. Considering 6 different angles (i.e. 0°, 30°, 60°, 90°, 120°, 150°) and 4 different loads (i.e. 1, 2, 4 and 6 Kg), the proposed algorithms are successful in estimating joint angles with accuracies above the chance level in all the conditions. However, when transfer from the known load condition to the unknown load condition, the average accuracy of the subject-dependent classifiers drop from 73.15% to 53% and 68.5% to 36.11% for KNN and NB respectively. Moreover, when transfer from the subject-dependent condition to the subject-independent condition when the carried load is unknown, the average accuracy drop from 53% and 24.7% for KNN. However, we do not observe any average loss in accuracy for the NB classifier.

It is important to mention that the results are obtained using a very small training size. Besides, the data acquisition system used in this study is a very low-cost system. Increasing the training size as well as extracting more informative features would improve the classification accuracy.

ACKNOWLEDGMENTS

The authors would like to thank Prof. Mohamed H.El-Mahlawy (Ret.), Head of Biomedical Engineering Department, Military Technical College, Egypt, for assisting in data collection by providing the department facilities, and Dr. Ahmed Onsy, UCLAN, United Kingdom, for assisting in the experimental process. Finally yet importantly, the authors would like to thank the participants who attended in this study.

REFERENCES

[1] B. D. Cheson, B. Pfistner, M. E. Juweid, R. D. Gascoyne, L. Specht, S. J. Horning, B. Coiffier, R. I. Fisher, A. Hagenbeek, E. Zucca *et al.*, "Revised response criteria for Malignant Lymphoma," *Journal of Clinical Oncology*, vol. 25, no. 5, pp. 579–586, 2007.

[2] R. Gopura, D. Bandara, J. Gunasekara, and T. Jayawardane, "Recent trends in EMG-based control methods for assistive robots," *Electrodiagnosis in New Frontiers of Clinical Research, InTech, DOI: 10.5772/56174*, pp. 237–268, 2013.

[3] R. M. Singh, S. Chatterji, and A. Kumar, "Trends and challenges in EMG based control scheme of exoskeleton robotsA review," *Int. J. Sci. Eng. Res*, vol. 3, pp. 933–40, 2012.

[4] H. Kawamoto and Y. Sankai, "Power assist method based on phase sequence and muscle force condition for HAL," *Advanced Robotics*, vol. 19, no. 7, pp. 717–734, 2005.

[5] P. Heo, G. M. Gu, S.-j. Lee, K. Rhee, and J. Kim, "Current hand exoskeleton technologies for rehabilitation and assistive engineering," *International Journal of Precision Engineering and Manufacturing*, vol. 13, no. 5, pp. 807–824, 2012.

[6] H. He and K. Kiguchi, "A study on EMG-based control of exoskeleton robots for human lower-limb motion assist," in *Proceeding of 6th International Special Topic Conference on Information Technology Applications in Biomedicine*, 2007, pp. 292–295.

[7] Y. M. Aung and A. Al-Jumaily, "Estimation of upper limb joint angle using surface EMG signal," *International Journal of Advanced Robotic Systems*, vol. 10, no. 10, p. 369, 2013.

[8] T. Kawase, T. Sakurada, Y. Koike, and K. Kansaku, "Estimating joint angles from biological signals for multi-joint exoskeletons," in *Proceeding of 2014 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 2014, pp. 1470–1474.

[9] Y. M. Aung and A. Al-Jumaily, "sEMG based ANN for shoulder angle prediction," *Procedia Engineering*, vol. 41,2012, pp. 1009–1015.

[10] A. H. Al-Timemy, G. Bugmann, J. Escudero, and N. Outram, "A preliminary investigation of the effect of force variation for myoelectric control of hand prosthesis," in *Proceeding of 35th IEEE International Conference on Engineering in Medicine and Biology Society (EMBC)*, 2013, pp. 5758–5761.

[11] X. Chen, X. Zhang, Z.-Y. Zhao, J.-H. Yang, V. Lantz, and K.-Q. Wang, "Hand gesture recognition research based on surface EMG sensors and 2D-accelerometers," in *Proceeding of 11th IEEE International Symposium on Wearable Computers*, 2007, pp. 11–14.

[12] Z. Tang, H. Yu, and S. Cang, "Impact of load variation on joint angle estimation from surface EMG signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 12, pp. 1342–1350, 2016.

[13] S. Thongpanja, A. Phinyomark, F. Quaine, Y. Laurillau, B. Wongkittisuksa, C. Limsakul, and P. Phukpattaranont, "Effects of window size and contraction types on the stationarity of biceps brachii muscle EMG signals," in *Proceeding of 7th International Convention on Rehabilitation Engineering and Assistive Technology*, 2013, p. 44.

[14] E. J. Rechy-Ramirez and H. Hu, "Bio-signal based control in assistive robots: A survey," *Digital Communications and Networks*, vol. 1, no. 2, pp. 85–101, 2015.

[15] M. J. Islam, Q. J. Wu, M. Ahmadi, and M. A. Sid-Ahmed, "Investigating the performance of naive-bayes classifiers and k-nearest neighbor classifiers," in *Proceeding of International Conference on Convergence Information Technology, 2007.* IEEE, 2007, pp. 1541–1546.

[16] A. M. Azab, A. Onsy, and M. H. El-Mahlawy, "Design and development of a low cost prosthetic arm control system based on sEMG signal," in *Proceeding of ASME 2015 International Mechanical Engineering Congress and Exposition*, 2015, pp. V003T03A080–V003T03A080.

[17] J. L. Echternach, *Introduction to Electromyography and nerve conduction testing*. SLACK Incorporated, 2003.