Testing the Performance of Linear Regressors Using Inertial Information Combined with sEMG to Minimize the Limb Position Effect in Proportional and Simultaneous Control of Lower Arm Prosthetics.

Simon Bruun, Oliver Thomsen Damsgaard, Martin Alexander Garenfeld, Irene Uriarte

***Abstract*—**

Electromyography (EMG) is widely used for controlling functional prosthetics. However, EMG signals for the same movements change with variations in limb position and lowers the accuracy in control schemes [?]. Most of the previous studies have utilized classification for pattern recognition when changing limb position, with a negative effect in performance. This study investigated the effect of limb position in a linear regression-based control scheme, when using Mean Absolute Value (MAV) and Logarithmic Variance (LogVar) as features. Seven (more now) able-bodied subjects were recruited for data acquisition, performing four wrist movements in three different limb positions. One regression model was build to recognize the different wrist movements under study, taking into account both features. The regressors were tested online in a virtual environment. The results showed that changes in limb position do not affect the control when linear regression model is trained with the features extracted. This is opposed to previous studies using classification as control scheme. Linear regression has the potential to be used in future control schemes for myoelectric prosthetics for use in daily life tasks.

***Keywords*—surface electromyography, inertial measurement unit, simultaneous and proportional myoelectric control, regression, hand motion classification, hand prosthetic**

I. INTRODUCTION

In recent years the development of EMG controlled prosthesis have advanced due to an increased interest in the area as well as a higher demand of better control of this prosthesis.[**?**] In the early years most EMG prosthetics functioned by only controlling one DOF by *on-off control*, mostly by linking antagonistic muscles to one DOF. This control provided a way to control more than one DOF, but not simultaneously. However, as demands would rise, more complex methods were introduced to the EMG scene. Classification methods enabled simultaneous control of more than one DOF, but gave rise to new problems; a wider range of control would give less accurate movements, and training the pattern recognition methods proved difficult, as the training could over-fit, causing extended use of the prosthetics to degrade in performance. [**?**].

It has been proved that regression techniques can be apply as a new mapping method to achieve simultaneous and proportional control of multiple DOFs[**?**]. Regression methods provide a continous value for each DOF based on the recorded EMG signal, while classification methods only decides upon a certain class. However there are still difficulties when prosthesis perform outside the clinical training environment[**?**]. Fougner et al.[**?**] noticed that majority of studies only take in account one limb position. It has been shown that some muscles are activated based on joint angles [**?**], even though the muscles are not involved in the movement of that joint, which can be explained by muscle-synergies existed between muscles. Variations in limb positions can have an impact on the robustness of EMG pattern recognition. In order to overcome this problem it has been suggested to combine EMG data as well as IMU data, to provide limb position information. Nevertheless this combination of data have only been investigated for classification methods. In this study we test the performance of linear regression methods combining EMG and IMU data for a simultaneous and proportional control of two DOFs in a lower-arm prothesis while the arm is located in different limb positions.

II. METHODS

A. Experimental Setup

EMG data was collected from (define number) able-bodied subjects. The subjects performed four different hand gestures. This study is only focus on two DOF, which are, flexion, extension, radial and ulnar deviation of the wrist. The order in the execution of the movements was the same for each subject. EMG signals were recorded with Myo armband, positioned in the right forearm of the subjects (all subjects right handed). The procedure was performed in three different limb positions. In order to avoid shoulder fatigue a relaxation period was given between trials. The subjects were instructed not to move the fingers during the data acquisition. The process was performed in a standing position.
Myo armband counts with eight medical grade stainless steel surface EMG sensors. Furthermore its nine axis IMU provides information about position and orientation of the arm combining three axis accelerometer, three axis gyroscope and three axis magnetometer.
In order to acquire the training data necessary to build the regressor, a graphical user interface (GUI) was implemented in MATLAB.

B. Preprocessing

For this study the EMG data acquired were filtered using a second-order Butterworth high-pass filter, cutoff frequency (f_c=10Hz), to avoid low frequency movement artefacts in the recorded signal.

C. Feature extraction

The features were extracted creating a sliding-window of 40 samples. Two different time domain features were extracted, MAV as well as LogVar. MAV represent the amplitud of the signal. It is defined as the average of the absolute values of the EMG signal and expresed as:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{1}$$

where N is the length of the signal, and x_i is the signal of i samples. The LogVar is a nonlinear transformation of the variance, which has been shown to behaves more linear than other time domain features. [**?**]

$$log(\sigma^2) = log(\frac{\sum_{i=1}^{N}(x_i-\mu)^2}{N}) \tag{2}$$

where N expresses the length of the signal, x_i is the i^th sample of the signal and μ is the mean.

D. Separability of data

Principal Component Analysis (PCA) was applied to be able to evaluate the quality of the features extracted from the EMG signals.

E. Data exclusion

Some of the subjects were not able to perform through the study properly. In order to ensure constant data those subjects were exclude.

F. Regression models

The acquired data was used to built the different regressors that had been implemented, one for each movement under study and for both features. Multivariate linear regression as an extension of simple linear regression had been applied as is shown in 3:

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i + \epsilon_i \tag{3}$$

where Y is the dependent variable, X_i are the independent variables, β_i is the regression coefficient in the sampled population, α is the predicted value of Y at $X = 0$ and ϵ is the error.

G. Regressor accuracy

Superimposition
In order to examine the performance of the regressors the estimations of the regressor and the actual data for the two different features extracted had been superimposed. Thereby the behave of the regressor can be shown at different intensities and movements. Consequently whether other regression methods should be considered to obtain a lower error.
RMSE
To meassure the accuracy of the regressor, Root Mean Squared Error (RMSE) was calculated. RMSE is a calculation of the standard deviation of the residuals, that is, the difference between the estimated and the actual values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{N}} \tag{4}$$

Where N is the length of the signal, y_i is the i^th variable of the actual data and $\hat{y_i}$ is the i^th output of the regressor. The RMSE will be done for the regressor of each movement.

III. RESULTS

something!!!

A. Separability of the data

B. Regression accuracy

IV. DISCUSSION

V. CONCLUSIONS

Linear regression methods were applied for the two different features extracted. We compared both performance, training the regressor with EMG data as well as a combination of EMG data and IMU data.

APPENDIX

Appendixes should appear before the acknowledgment.

ACKNOWLEDGMENT

The preferred spelling of the word acknowledgment in America is without an e after the g. Avoid the stilted expression, One of us (R. B. G.) thanks . . . Instead, try R. B. G. thanks. Put sponsor acknowledgments in the unnumbered footnote on the first page.

References are important to the reader; therefore, each citation must be complete and correct. If at all possible, references should be commonly available publications.

REFERENCES

[1] G. O. Young, Synthetic structure of industrial plastics (Book style with paper title and editor), in Plastics, 2nd ed. vol. 3, J. Peters, Ed. New York: McGraw-Hill, 1964, pp. 1564.

[2] W.-K. Chen, Linear Networks and Systems (Book style). Belmont, CA: Wadsworth, 1993, pp. 123135.

[3] H. Poor, An Introduction to Signal Detection and Estimation. New York: Springer-Verlag, 1985, ch. 4.

[4] B. Smith, An approach to graphs of linear forms (Unpublished work style), unpublished.

[5] E. H. Miller, A note on reflector arrays (Periodical styleAccepted for publication), IEEE Trans. Antennas Propagat., to be publised.

[6] J. Wang, Fundamentals of erbium-doped fiber amplifiers arrays (Periodical styleSubmitted for publication), IEEE J. Quantum Electron., submitted for publication.

[7] C. J. Kaufman, Rocky Mountain Research Lab., Boulder, CO, private communication, May 1995.

[8] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, Electron spectroscopy studies on magneto-optical media and plastic substrate interfaces(Translation Journals style), IEEE Transl. J. Magn.Jpn., vol. 2, Aug. 1987, pp. 740741 [Dig. 9th Annu. Conf. Magnetics Japan, 1982, p. 301].

[9] M. Young, The Techincal Writers Handbook. Mill Valley, CA: University Science, 1989.

[10] J. U. Duncombe, Infrared navigationPart I: An assessment of feasibility (Periodical style), IEEE Trans. Electron Devices, vol. ED-11, pp. 3439, Jan. 1959.

[11] S. Chen, B. Mulgrew, and P. M. Grant, A clustering technique for digital communications channel equalization using radial basis function networks, IEEE Trans. Neural Networks, vol. 4, pp. 570578, July 1993.

[12] R. W. Lucky, Automatic equalization for digital communication, Bell Syst. Tech. J., vol. 44, no. 4, pp. 547588, Apr. 1965.

[13] S. P. Bingulac, On the compatibility of adaptive controllers (Published Conference Proceedings style), in Proc. 4th Annu. Allerton Conf. Circuits and Systems Theory, New York, 1994, pp. 816.

[14] G. R. Faulhaber, Design of service systems with priority reservation, in Conf. Rec. 1995 IEEE Int. Conf. Communications, pp. 38.

[15] W. D. Doyle, Magnetization reversal in films with biaxial anisotropy, in 1987 Proc. INTERMAG Conf., pp. 2.2-12.2-6.

[16] G. W. Juette and L. E. Zeffanella, Radio noise currents n short sections on bundle conductors (Presented Conference Paper style), presented at the IEEE Summer power Meeting, Dallas, TX, June 2227, 1990, Paper 90 SM 690-0 PWRS.

[17] J. G. Kreifeldt, An analysis of surface-detected EMG as an amplitude-modulated noise, presented at the 1989 Int. Conf. Medicine and Biological Engineering, Chicago, IL.

[18] J. Williams, Narrow-band analyzer (Thesis or Dissertation style), Ph.D. dissertation, Dept. Elect. Eng., Harvard Univ., Cambridge, MA, 1993.

[19] N. Kawasaki, Parametric study of thermal and chemical nonequilibrium nozzle flow, M.S. thesis, Dept. Electron. Eng., Osaka Univ., Osaka, Japan, 1993.

[20] J. P. Wilkinson, Nonlinear resonant circuit devices (Patent style), U.S. Patent 3 624 12, July 16, 1990.