sEMG Signal Separation for Wrist Angle Estimation

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Abstract— This document

1. Introduction

Myoelectric signal activity had been known to increase with the muscle movement intensity[1]. With electromyography (EMG), myoelectric signal can be recorded and aid in researches including gait analysis[2], fatigue evaluation[3], motor neuron disease diagnosis[4], and prosthesis control[5]–[8].

Surface EMG (sEMG) is widely employed in EMG signal recording, because of its ease of use and non-invasiveness. sEMG records the summation of action potential generated by a group of motor neurons, as the muscle tissue between the motor neurons and surface electrode acts as a volume conductor. sEMG signal is affected by the crosstalk of multiple muscle groups[9].

sEMG signal can be assumed to be linearly mixed action potential originating from different muscle groups, the effect of crosstalk can be mitigated through the use of blind signal separation (BSS) algorithm. A popular BSS method, Independent Component Analysis (ICA), were employed to increase the classification accuracy in gesture recognition[10]. However, since the probability distribution of a sEMG signal is close to Gaussian distribution, ICA cannot be applied effectively to separate the action potential from sEMG signal[11]. ICA was mostly used to remove motion artefacts[12].

Crosstalk between muscle groups can be easily observed from the forearm. Multiple muscle groups are present in the forearm, in charge of functions including wrist motion and hand gestures[13].

This paper focus on the estimation of wrist angle with the sEMG signal recorded from the forearm. For the experiment, two degrees of wrist movements are chosen: flexion/extension and pronation/supination.

To mitigate the effect of crosstalk, this paper proposed the separation of sEMG signal power with two BSS methods, and compare their results.

The two BSS methods are Non-negative ICA (nICA) [14] and Temporal Decorrelation Source Separation (TDSEP) [15]. nICA treats the data as a group of data point and minimize the mutual information of the data; TDSEP decorrelates multi-channel time series, minimizing the correlation between time series.

Relationship between sEMG signal and muscle tension is highly non-linear[16]. Neural networks are utilized in previous research to model the non-linear relationship[5], [8], [17]–[21]. In this thesis, Long Short Term Memory (LSTM) is used to estimate the wrist angle. LSTM is a type of Recurrent Neural Network (RNN) that includes internal memory cell inside the network. The internal memory can help LSTM model time series, which made it suitable for wrist angle estimation.

1. Methodology

The proposed sEMG wrist angle estimation system consists of feature extraction, signal separation, and angle estimation. The following describes the detail of these steps.

1. sEMG Signal Feature Extraction

In this thesis, windowed Root Mean Square (RMS) is used as the feature for wrist angle estimation. RMS can be used to extract signal power. RMS of sEMG signal represents the muscle activity, and is calculated using the following formula.

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|  | (1) |

Where is the sEMG recording at time , and is the number of sample point in 200 milliseconds. The result of windowed RMS is shown in Fig. 1, sEMG signal after windowed RMS is smoother and non-negative.

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| Fig. 1 Windowed RMS of sEMG  (a) raw sEMG signal (b) windowed RMS sEMG signal |

1. sEMG Signal Separation

sEMG signal originates from deep within the muscle, affected by the crosstalk of multiple muscle groups[9]. Assuming the mixture of sEMG signal is linearly mixed, it is possible to separate the signal between different muscle groups. The technique is called Blind Source Separation (BSS). If the measured signal is linearly mixed, it can be expressed as

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|  | (2) |

where is the sEMG recording, is the original myoelectric signal, and is the mixing matrix. In sEMG recording, mixing matrix models how myoelectric signal mixed within the muscle. Since both the mixing matrix and source signal is unknown, BSS is performed to search for the un-mixing matrix, and independent components are retrieved. Un-mixing matrix translates the mixed signal so that

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|  | (3) |

In this thesis, two BSS methods are tested and compared. The two BSS methods are Non-negative ICA (nICA) [14] and Temporal Decorrelation Source Separation (TDSEP) [15].

1. Non-negative ICA

In nICA[14], the original signal is assumed to be non-negative, which is true in the case of muscle power. First, ZCA whitening is performed on the recorded signal

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|  | (4) |

where is the whitened signal with the covariance matrix being an identity matrix . The whitening matrix can be found by performing Eigendecomposition on the covariance matrix of . To eliminate the mutual information, nICA rotates the whitened signal with rotation matrix

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|  | (5) |

where is the un-mixed signal. The cost function of the rotation matrix is expressed as

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|  | (6) |

where , the value is zero when is negative. The cost decreases as more samples are rotated to be non-negative. After rotation, the resulting signal is the un-mixed signal.

1. Temporal Decorrelation Source Separation

In TDSEP[15], time series are separated by minimizing the cross-correlation across multiple time lags. To find the optimal un-mixing matrix , the cost function is defined as

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|  | (7) |

where is the channel of the recorded signal, is a series of time lags, and denotes time average. A way to find the un-mixing matrix is to perform gradient descent to minimize the cost function with respect to . However, gradient descent is computationally costly, [15] proposed the following method to find the approximation of .

First, ZCA whitening is performed on the recorded signal , the result is the whitened signal . Correlation matrices are found under different time lag, the collection of these matrices is . Lastly, using the method proposed by [22], a rotation matrix can be found by simultaneously diagonalizing all matrices in . The rotation matrix ***Q*** is the approximation of the optimal un-mixing matrix .

1. Long Short-Term Memory Neural Network

In this paper, Long Short-Term Memory (LSTM) neural network is used to model the relationship between sEMG signal and wrist angle. The architecture of LSTM used in this paper is described by Graves and Schmidhuber[23], shown in Fig. 2

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| Fig. 2 LSTM architecture. Reprinted from [24] |

Two separate LSTM networks are used to estimate the angle on the two degrees of wrist movements: flexion/extension and pronation/supination. Each with one input cell, six LSTM block, and one output cell. The activation function for is the hyperbolic tangent function, sigmoid function for LSTM blocks, and identity activation function for output cell.

1. Experiment Protocol

In this paper, 4-channel and 6-channel sEMG are tested. Each channel is in active differential electrode configuration with an inter-electrode distance of 10mm, as shown in Fig. 3. The sEMG signal is filtered with low pass (<450Hz) and high pass (>10Hz) filter, then amplified with a gain of 1400. The signal is recorded with a sampling rate of 2660Hz.

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| Fig. 3 Active electrode |

Three subjects (age 22~24) are tested. The subjects were asked to place the forearm flat on the table with palm facing down. The subjects are asked to perform four types for wrist gesture: flexion/extension and pronation/supination. Each movement is repeated 20 times for three rounds (60 segments per gesture), with five minutes of rest between rounds. A gesture is performed in a six second window, with two seconds of rest, followed by two seconds of motion, then two seconds of rest.

For 4-channel sEMG, two configurations are tested twice; For 6-channel sEMG, three configurations are tested once. The electrodes are placed on the thickest part of the forearm (~5cm from the elbow), forming an equidistant circular configuration. With the palm facing down, we define the top of the arm perpendicular to the ground as 0°; In 4-channel sEMG, the electrodes are placed from 0° and 45°; In 6-channel sEMG, the electrodes are placed from 0°, 15°, and 30°. The five configurations are shown in Fig. 4.

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| Fig. 4 Electrode placement configurations  (a) 4-ch configurations: 0° and 45° (b) ­­6-ch configurations: 0°, 15°, 30° |

sEMG signals are recorded with Teensy3.2 with Processing-3. The data are pre-processed with Matlab, then a LSTM implemented in C is trained and tested.

Three signal processing procedure is compared. The first is RMS-only, shown in Fig. 5. In RMS-only, windowed RMS is performed on the recorded sEMG, then downsampled to 35Hz to reduce data dimension. The second procedure is RMS-nICA, shown in

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| Fig. 5 RMS-only Signal Processing Procedure |

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1. Level-1 Heading: A level-1 heading must be in Small Caps, centered and numbered using uppercase Roman numerals. For example, see heading “III. Page Style” of this document. The two level-1 headings which must not be numbered are “Acknowledgment” and “References”.
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TABLE I  
Font Sizes for Papers

|  |  |  |  |
| --- | --- | --- | --- |
| Font Size | Appearance (in Time New Roman or Times) | | |
| Regular | Bold | Italic |
| 8 | table caption (in Small Caps),  figure caption,  reference item |  | reference item (partial) |
| 9 | Contact author email address (in Courier), cell in a table | abstract body | abstract heading (also in Bold) |
| 10 | level-1 heading (in Small Caps),  paragraph |  | level-2 heading,  level-3 heading,  author affiliation |
| 11 | author name |  |  |
| 24 | title |  |  |

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When referring to a reference item, please simply use the reference number, as in [2]. Do not use “Ref. [3]” or “Reference [3]” except at the beginning of a sentence, e.g. “Reference [3] shows …”. Multiple references are each numbered with separate brackets (e.g. [2], [3], [4]–[6]).

Examples of reference items of different categories shown in the References section include:

* example of a book in [1]
* example of a book in a series in [2]
* example of a journal article in [3]
* example of a conference paper in [4]
* example of a patent in [5]
* example of a website in [6]
* example of a web page in [7]
* example of a databook as a manual in [8]
* example of a datasheet in [9]
* example of a master’s thesis in [10]
* example of a technical report in [11]
* example of a standard in [12]

1. Conclusions

This template is partly based on the template used for the 19th ISSTT (Groningen, 2008) and the 21st ISSTT (Oxford, 2010), which was in turn based on “Sample IEEE Paper for A4 Page Size” provided by courtesy of Causal Productions (www.causalproductions.com).

Acknowledgment

The heading of the Acknowledgment section and the References section must not be numbered.

References

[1] V. T. Inman, J. B. deC. M. Saunders, and L. C. Abbott, “Observations on the Function of the Shoulder Joint,” *JBJS*, vol. 26, no. 1, p. 1, Jan. 1944.

[2] A. D. Stefano, J. H. Burridge, V. T. Yule, and R. Allen, “Effect of Gait Cycle Selection on EMG Analysis During Walking in Adults and Children with Gait Pathology,” *Gait Posture*, vol. 20, no. 1, pp. 92–101, Aug. 2004.

[3] M. Cifrek, V. Medved, S. Tonković, and S. Ostojić, “Surface EMG Based Muscle Fatigue Evaluation in Biomechanics,” *Clin. Biomech. Bristol Avon*, vol. 24, no. 4, pp. 327–340, May 2009.

[4] J. J. Chen, T. Y. Sun, T. H. Lin, and T. S. Lin, “Spatio-Temporal Representation of Multichannel EMG Firing Patterns and Its Clinical Applications,” *Med. Eng. Phys.*, vol. 19, no. 5, pp. 420–430, Jul. 1997.

[5] C. Castellini and P. van der Smagt, “Surface EMG in Advanced Hand Prosthetics,” *Biol. Cybern.*, vol. 100, no. 1, pp. 35–47, Jan. 2009.

[6] Z. O Khokhar, Z. Xiao, and C. Menon, “Surface EMG Pattern Recognition for Real-Time Control of a Wrist Exoskeleton,” *Biomed. Eng. Online*, vol. 9, p. 41, Aug. 2010.

[7] Y. M. Aung and A. Al-Jumaily, “Estimation of Upper Limb Joint Angle Using Surface EMG Signal,” *Int. J. Adv. Robot. Syst.*, vol. 10, no. 10, p. 369, Jan. 2013.

[8] J. L. G. Nielsen, S. Holmgaard, Ning Jiang, K. B. Englehart, D. Farina, and P. A. Parker, “Simultaneous and Proportional Force Estimation for Multifunction Myoelectric Prostheses Using Mirrored Bilateral Training,” *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3, pp. 681–688, Mar. 2011.

[9] D. A. Winter, A. J. Fuglevand, and S. E. Archer, “Crosstalk in Surface Electromyography: Theoretical and Practical Estimates,” *J. Electromyogr. Kinesiol. Off. J. Int. Soc. Electrophysiol. Kinesiol.*, vol. 4, no. 1, pp. 15–26, 1994.

[10] G. R. Naik, D. K. Kumar, V. P. Singh, and M. Palaniswami, “Hand Gestures for HCI Using ICA of EMG,” in *Proceedings of the HCSNet Workshop on Use of Vision in Human-computer Interaction - Volume 56*, Darlinghurst, Australia, Australia, 2006, pp. 67–72.

[11] G. R. Naik, D. K. Kumar, and M. Palaniswami, “Multi Run Ica and Surface EMG Based Signal Processing System for Recognising Hand Gestures,” in *2008 8th IEEE International Conference on Computer and Information Technology*, Sydney, Australia, 2008, pp. 700–705.

[12] Qin Zhang, Caihua Xiong, and Wenbin Chen, “Continuous Motion Decoding from EMG Using Independent Component Analysis and Adaptive Model Training,” in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, IL, 2014, pp. 5068–5071.

[13] Susan Standring, *Gray’s Anatomy: The Anatomical Basis of Clinical Practice*. Elsevier Limited, 2016.

[14] M. D. Plumbley, “Algorithms for Nonnegative Independent Component Analysis,” *IEEE Trans. Neural Netw.*, vol. 14, no. 3, pp. 534–543, May 2003.

[15] A. Ziehe and K.-R. Müller, “TDSEP — an Efficient Algorithm for Blind Separation Using Time Structure,” in *ICANN 98*, 1998, pp. 675–680.

[16] Roberto Merletti and Philip J. Parker, *Electromyography: Physiology, Engineering, and Non-Invasive Applications*. Wiley-IEEE Press, 2004.

[17] N. Jiang, J. L. Vest-Nielsen, S. Muceli, and D. Farina, “EMG-Based Simultaneous and Proportional Estimation of Wrist/Hand Kinematics in Uni-Lateral Trans-Radial Amputees,” *J. NeuroEngineering Rehabil.*, vol. 9, no. 1, p. 42, Jun. 2012.

[18] M. Gazzoni, N. Celadon, D. Mastrapasqua, M. Paleari, V. Margaria, and P. Ariano, “Quantifying Forearm Muscle Activity during Wrist and Finger Movements by Means of Multi-Channel Electromyography,” *PLoS ONE*, vol. 9, no. 10, Oct. 2014.

[19] B. Hudgins, P. Parker, and R. N. Scott, “A New Strategy for Multifunction Myoelectric Control,” *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, Jan. 1993.

[20] D. Hofmann, N. Jiang, I. Vujaklija, and D. Farina, “Bayesian Filtering of Surface EMG for Accurate Simultaneous and Proportional Prosthetic Control,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 12, pp. 1333–1341, Dec. 2016.

[21] S. El-Khoury *et al.*, “EMG-Based Learning Approach for Estimating Wrist Motion,” in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Milan, 2015, pp. 6732–6735.

[22] J. Cardoso and A. Souloumiac, “Jacobi Angles for Simultaneous Diagonalization,” *SIAM J. Matrix Anal. Appl.*, vol. 17, no. 1, pp. 161–164, Jan. 1996.

[23] A. Graves and J. Schmidhuber, “Framewise Phoneme Classification with Bidirectional LSTM and Other Neural Network Architectures,” *Neural Netw.*, vol. 18, no. 5, pp. 602–610, Jul. 2005.

[24] K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink, and J. Schmidhuber, “LSTM: A Search Space Odyssey,” *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 10, pp. 2222–2232, Oct. 2017.