sEMG Signal Separation for Wrist Angle Estimation

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Abstract— In this paper, surface EMG signal (sEMG) is used to estimate the wrist angle. sEMG signal reflects the effort of the muscle. When measuring sEMG signal, a single electrode can receive EMG signal from multiple muscle group, affected by the cross-talk from muscles Previous research applied ICA algorithm to sEMG signal to separate EMG signal from different muscle group. However, EMG signal source is a highly gaussian signal source, ICA is ineffective. This thesis devised a sEMG signal power separation method, windowed RMS is used to extract sEMG signal power, then two signal separation algorithm (TDSEP and nICA) is applied, avoiding the problem of high gaussianity. Using the proposed wrist angle estimation system, we evaluate the performance improvement of using two signal separation algorithm in wrist angle estimation. In 4-channel sEMG, both algorithms improve the estimation accuracy (quantified by RMSE) by 15~20%; in 6-channel sEMG, the estimation accuracy is improved by 7~16%.

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 EMG signal source is close to Gaussian distribution[11], ICA cannot be applied effectively to separate the action potential from sEMG signal[12]. ICA was mostly used to remove motion artefacts[13].

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[14].

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) [15] and Temporal Decorrelation Source Separation (TDSEP) [16]. 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[17]. Neural networks are utilized in previous research to model the non-linear relationship[5], [8], [18]–[22]. 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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| E:\Ubuntu\sEMG\Paper\pic\wRMS.png |
| 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

|  |  |
| --- | --- |
|  | (3) |

In this thesis, two BSS methods are tested and compared. The two BSS methods are Non-negative ICA (nICA) [15] and Temporal Decorrelation Source Separation (TDSEP) [16].

1. Non-negative ICA

In nICA[15], 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[16], 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, [16] 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 [23], 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[24], shown in Fig. 2

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| C:\Users\Dymnz\Desktop\Capture.PNG |
| Fig. 2 LSTM architecture. Reprinted from [25] |

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. An Inertial Measurement Unit (IMU) is mounted on the hand of the subject, as shown in Fig. 4. The IMU provides information on specific force, angular rate, and magnetic field of the surrounding. This information is used to calculated wrist angle as the ground truth.

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| Fig. 3 Active electrode |

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| Fig. 4 IMU placement |

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. 5.

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| Fig. 5 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. The data is analysed in 5-fold cross-validation, where the data is split into 5 groups; in each round, four of the groups are used to train the LSTM model, and the remaining one is used to test the performance of the model.

Three signal processing procedure is compared. The first is RMS-only, shown in Fig. 6. In RMS-only, windowed RMS feature extraction is performed on the recorded training set and testing set. The processed data are then downsampled to 35Hz to reduce data dimension.

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| Fig. 6 RMS-only Signal Processing Procedure |

The second procedure is RMS-nICA, shown in Fig. 7. In RMS-nICA, an additional ICA dataset is used to find the nICA de-mixing matrix. As before, windowed RMS is performed on training set and testing set, then the nICA de-mixing matrix is applied. After de-mixing, the data is downsampled to 35Hz to reduce data dimension. The third procedure is RMS-TDSEP, shown in Fig. 8. In RMS-TDSEP, TDSEP is used onto ICA dataset to calculate the de-mixing matrix. After windowed RMS for training set and testing set is de-mixed with TDSEP de-mixing matrix. The data is then downsampled to 35Hz to reduce data dimension.

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| Fig. 7 RMS-nICA Signal Processing Procedure |

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| Fig. 8 RMS-TDSEP Signal Processing Procedure |

After pre-processing, LSTM is trained with training set. LSTM estimates the wrist angle of the testing set, then Root Mean Square Error (RMSE) is calculated between the estimation and ground truth using the following equation

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| --- | --- |
|  | (8) |

where is the angle ground truth at time , and is the estimated angle at time . The RMSE is calculated for the whole six seconds for each segment, the unit is in degree (°).

1. Experiment Results

TABLE I  
4-ch sEMG - Average RMSE in degree

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Flexion | Extension | Pronation | Supination |
| 0° - RMS | 5.044 | 5.012 | 10.215 | 10.747 |
| 0° - nICA | 4.698 | 4.721 | 8.432 | 8.785 |
| 0° - TDSEP | 4.805 | 4.835 | 8.718 | 9.075 |
| 45°- RMS | 5.128 | 5.064 | 11.576 | 12.390 |
| 45°- nICA | 5.203 | 5.135 | 9.332 | 10.483 |
| 45°- TDSEP | 5.149 | 5.091 | 9.541 | 10.424 |

TABLE II  
4-ch sEMG – Improvements comparing to RMS-only

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Flexion | Extension | Pronation | Supination |
| 0° - nICA | -6.85% | -5.80% | -17.45% | -18.26% |
| 0° - TDSEP | -4.74% | -3.52% | -14.65% | -15.55% |
| 45°- nICA | 1.46% | 1.41% | -19.38% | -15.39% |
| 45°- TDSEP | 0.41% | 0.55% | -17.58% | -15.87% |

Comparing the estimation error of the three signal processing procedures. In 4-ch sEMG, the electrodes are placed from 0° and 45°. Two experiments for each of the configurations are averaged, as shown in TABLE I. For the two electrode placement configurations, placing electrode from 0° yields better estimation result comparing to 45°.

In 4-ch sEMG, the RMS-only procedure has the worst performance, RMS-nICA and RMS-TDSEP have similar performance. Pronation/supination have higher RMSE comparing to flexion/extension, as seen in previous research[26]. For flexion/extension, the RMSE for RMS-only is already low, the improvements for both nICA and TDSEP are limited. For pronation/supination, the improvements for nICA and TDSEP is 15~20%, as shown in TABLE II.

TABLE III  
6-ch sEMG - Average RMSE

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Flexion | Extension | Pronation | Supination |
| 0° - RMS | 4.578 | 4.427 | 6.775 | 8.181 |
| 0° - nICA | 5.220 | 5.003 | 6.199 | 7.009 |
| 0° - TDSEP | 4.899 | 4.761 | 6.100 | 6.868 |
| 15°- RMS | 4.854 | 4.758 | 8.023 | 9.317 |
| 15°- nICA | 4.905 | 4.852 | 7.437 | 8.226 |
| 15°- TDSEP | 4.710 | 4.665 | 7.316 | 8.104 |
| 30°- RMS | 5.103 | 5.029 | 9.198 | 10.302 |
| 30°- nICA | 5.733 | 5.573 | 7.653 | 8.826 |
| 30°- TDSEP | 5.191 | 5.022 | 7.699 | 8.820 |

TABLE IV  
6-ch sEMG – Improvements comparing to RMS-only

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| --- | --- | --- | --- | --- |
|  | Flexion | Extension | Pronation | Supination |
| 0° - nICA | 14.02% | 13.01% | -8.49% | -14.33% |
| 0° - TDSEP | 7.00% | 7.56% | -9.96% | -16.05% |
| 15°- nICA | 1.06% | 1.98% | -7.30% | -11.71% |
| 15°- TDSEP | -2.97% | -1.96% | -8.81% | -13.02% |
| 30°- nICA | 12.35% | 10.81% | -16.79% | -14.33% |
| 30°- TDSEP | 1.73% | -0.13% | -16.29% | -14.38% |

In 6-ch sEMG, the electrodes are placed from 0°, 15°, and 30°. The three configurations are tested once each, as shown in TABLE III. We observed that the estimation error is the lowest in 0° configuration, with 30° configuration having the highest error.

Similar to 4-ch sEMG, in 6-ch sEMG, RMS-only procedure has the worst performance of all. Estimation error for pronation/supination is higher than flexion/extension. For flexion/extension, the error for RMS-only is already low, nICA produces worst result, increasing the error. For pronation/supination, both nICA and TDSEP improves the estimation by 7~16%, as shown in TABLE IV.

Overall, nICA and TDSEP yields similar result in 4-ch sEMG. In 6-ch sEMG, TDSEP yields slightly better result comparing to nICA, with nICA increasing the error in two cases.

1. Conclusion

This paper proposed a method for sEMG signal separation. By first extracting sEMG signal power with windowed RMS, sEMG signal from different muscle groups can be separated using nICA and TDSEP. With the proposed signal separation method, LSTM neural network is utilized to model the relationship of sEMG and wrist angle. We compare the performance improvement of nICA and TDSEP in wrist angle estimation. Both nICA and TDSEP improves estimation error, with TDSEP being slightly better in 6-ch sEMG. In 4-ch sEMG, estimation error is improved by 15~20%; In 6-ch nICA and TDSEP improves the estimation error by 7~16%. We also found that increasing the number of electrode from four to six improves the estimation, even though only four muscle groups are activated while performing the four gesture. For real-world application, we recommend using 6-ch sEMG combined with TDSEP.

For future work, we wish to incorporate the signal separation method into array electrodes. In this paper we compared two signal separation method, more signal separation method may be considered in the future. For neural network architecture, the LSTM model used in the paper may be improved, other estimator may also be used.

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