A SSA-based de-noising technique for surface electromyography signals

Xuanliang Deng, Kang Wang

School of Information Engineering

Wuhan University of Technology,China

*dengxuanliang@whut.edu.cn

Keywords: Singular spectrum analysis; Surface electromyography; De-noising; Bioinformatics

Abstract. The surface electromyography(sEMG) signal emanates when people contract their muscles. The sEMG signal contains plenty of information about muscle activity. Therefore,it can be used in activity recognition, which makes great contribution to medical devices, e.g., protheses or orthoses control systems. Here,a de-noising technique is presented which applies singular spectrum analysis(SSA) to de-noise sEMG signals. The principle of SSA is to decompose the original time series into a set of additive time series in which noise can be easily distinguished from the useful signal. Unlike transform-based algorithms, such as discrete wavelet transform, SSA is a time-series analysis algorithm which is completely driven by signal itself. This data-driven nature makes SSA very useful for sEMG signal de-noising.

1 Introduction

The surface Electromyography signal is a low amplitude signal that emanates when people contra-ct their muscles[1]. sEMG signal can reflect the levels and patterns of muscle activation and distinguish active and passive movements[2]. However, it can be easily contaminated by various noise in the environment because of its low amplitude.

The original application of SSA was to extract trends from climatic and geophysical time series and to identify periodic motion in complex dynamical systems[3]. Because of its data-driven nature, SSA has been an efficient method to smooth raw kinematic signals and as a good technique to detect the onset of EMG signals recently[4,5]. Unlike other transform-based algorithms, SSA is totally based on the signal itself[6]. Therefore, it can be applied to any time series with complex structure. By decomposing the original sEMG signal into a number of additive components, including slowly varying trends, oscillatory components and unstructured noise, SSA can help us to reconstruct only the useful sEMG information contained in the whole signal. Compared with other traditional de-noising methods, SSA can better filter the low frequency noise and retain as much signal power as possible of the region of interest in frequency spectrum.

2 The Principle of SSA Algorithm

Singular spectrum analysis(SSA) belongs to principle components analysis[7]. It was first put forward by Broomhead and his colleagues. This method based on singular value decomposition of matrices, is always used to de-noise chaotic signal and to predict suitable models. SSA has good real-time characteristics and reduces amount of calculation[8], while the accuracy of reconstructed signal has improved.

Let time series $x(i)$ be the sEMG signal collected from electrodes, $i = 1,2,3...L$,while L represents the length of series x(i). Let m be the embedding dimensions. Let τ be the time delay. According to the embedding theorem, the $m \times n$ phase space of time series x(i) is:

$$X_k = [x(k), x(k+1), x(k+2r), ...x(k+(m-1)\tau)]^T, \quad (1)$$

while k =1,2,3,...,n, n = L- (m-1) τ . Trajectory matrix $X=[X_1,X_2,...,X_n]$ represent n coordinate points in phase space,which consist one signal trajectory. Let C be the Covariance matrix of matrix X:

$$C=XX^T/n. \tag{2}$$

Decomposing the singular value of Covariance matrix C, we have a group of non-negative singular values e(i), where i =1,2,...,m. Sort these singular values in decreasing order to consist singular spectrum,which shows the ratio of power of each signal component to the whole systems. When a signal component has a relatively large singular value, it is more likely to be the useful information contained in sEMG signal[9]. On the contrary, if a component has small value singular value, we always regard it as noise introduced from environment.The corresponding eigenvector of e_k is called empirical orthogonal function(EOF). The k^{th} principle component is defined as the orthogonal projection coefficient of original series x(i) on E_k :

$$a_i^k=\sum_{j=1}^{m}x_{i+j}E_j^k,(0\le i\le L-m). \tag{3}$$

If each principle component and empirical orthogonal function are known, then the signal can be reconstructed according to the formula below:

$$x_{i+j}=\sum_{k=1}^{m}a_i^kE_j^k,(1\le j\le m). \tag{4}$$

3 Simulation study

3.1 The process of singular spectrum analysis

The processes of sEMG signal de-noising based on SSA are shown in fig.1.

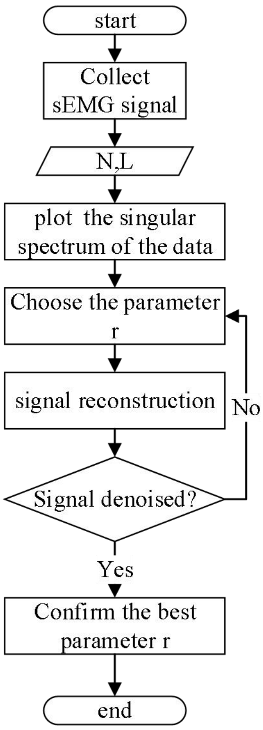

fig.1:The process of the sEMG signal de-noising based on SSA

The sEMG signal is collected by four surface electrodes and transmitted to the signal process circuit by the transmission line. In signal process circuit, it will be sampled and amplified. To use SSA, we need to choose window length L and data length N. Next, we need to plot the singular spectrum of data and base on this to choose a suitable parameter r,which is the critical point between signal and noise, to reconstruct signal components[10].We will need to try different values of r in order to have the best effect of de-nosing.

3.2 Plotting singular spectrum

Let the length of the sampled data N=1000.Generally, the length of the window is less than half of the data length. let L be 50. The singular spectrum of channel one, whose muscle is at the resting state, and channel four, whose muscle is at the excited state are shown in fig.2 and fig.3.

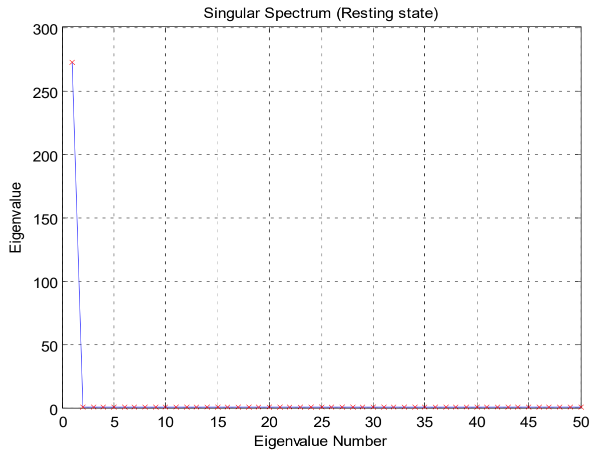

fig.2: The singular spectrum of sEMG signal at resting state(L=50)

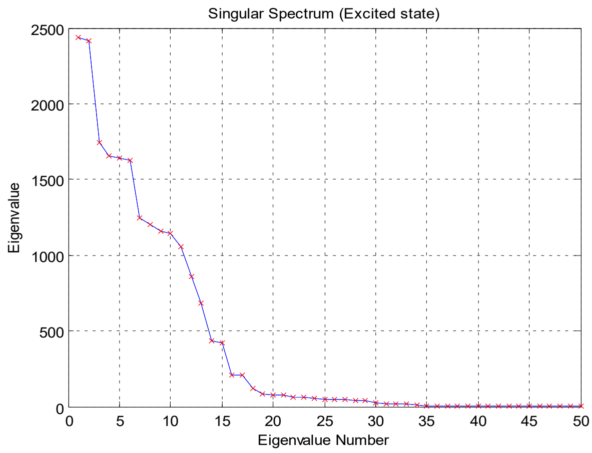

fig.3: The singular spectrum of sEMG signal at excited state(L=50)

It is clear in fig 2 that only the first data point represents the principle component of the signal. The eigenvalue of the rest data points are all zero.Reconstructing the first eigenvalue will be enough to restore the original signal. Under this circumstances, singular spectrum analysis would be an ideal method to de-noise the sEMG signal at resting state. In fig 3,the singular spectrum of the signal with laddering nature shows that we need to choose a parameter r as the critical point between principle signal and noise. Let r=20,those eigenvalues whose numbers are larger than 20 would be regarded as noise and we only use the first 20 points to reconstruct the original signal. A suitable value of r would contribute a lot to the final de-noising effect. As most of our test data are collected when the muscles are in excited state,we will mainly discuss the application of SSA for sEMG signal at excited state in the following paragraph.

Let L be 300 in order to see the trend of the singular spectrum more clearly.

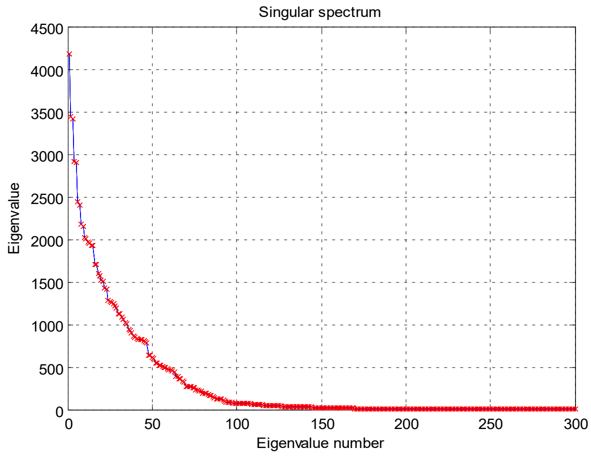

fig.4: The singular spectrum of sEMG signal at excited state(L=300)

From fig.4,we can see that the principle component of original sEMG signal is concentrated at the first 50 points.That is,for the points whose eigenvalue is relatively large,we can regard them as useful information contained in the signal.On the contrary, the points after number 125 all have small eigenvalues.Therefore,they can be regarded as noise[11].The value of the parameter r has significant effect on the accuracy of the reconstructed signal.

3.3 confirm a best value of parameter r

The next step is to choose a suitable value for parameter r.Based on the discussion above,the minimum value of r will be 50 and maximum of it maybe 125.We will try 6 different values of r and finally compare the results of residual signal spectrum in order to confirm value of r. First Let r be 50, its reconstructed signals and residual signals are shown in fig.5.

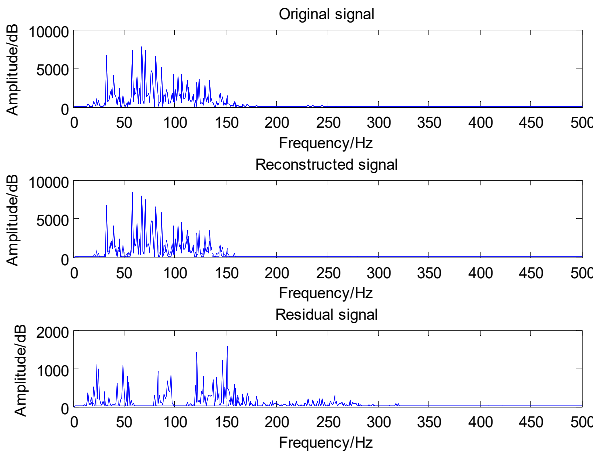

fig.5: Three signal spectrum when r =50

One criterion to choose a suitable value of r is to look at the average signal power spectral density of three frequency bands: 0 to 50Hz, 51 to 150Hz and 151 to 500Hz.We need to find a value of r to have average power as large as possible in both 0 to 50 Hz and 151 to 500 Hz, and average power as small as possible in the middle frequency band. Let r be 50,65,80,95,110,125, respectively,their average power in three bands are shown in Table I.

parameter r / average power / frequency band	50	65	80	95	110	125
0-50	160.6367	65.5513	27.0187	11.4374	3.5597	1.4801
51-150	184.6416	72.8193	7.9884	0.0920	0.0114	0.0164
151-500	39.6384	34.4986	30.5259	22.3951	16.9988	11.5995

Table I: Average signal power for different values of parameter r

Generally, the frequency of sEMG signal is usually between 10 to 500 Hz and the power of sEMG signal is mainly concentrated on 50 to 150 Hz[12]. The components out of this range are regarded as noise components. Therefore, when r=50/65/80, there are lots of signal power lost in residual signal in the region of 51 to 150Hz. When r=95/110/125, the spectrum of residual signal concentrates on 0 to 50Hz and 150 to 500 Hz is far smaller than the original signal,which can not be a good choice. Therefore, an ideal value of r would be between 80 to 95. After many trials,we finally find that when r =82, the sEMG signal will be perfectly de-noised. Three average signal power are 25.3616, 0.7591, 30.2868, respectively.The signal spectrum is shown in figure 6.

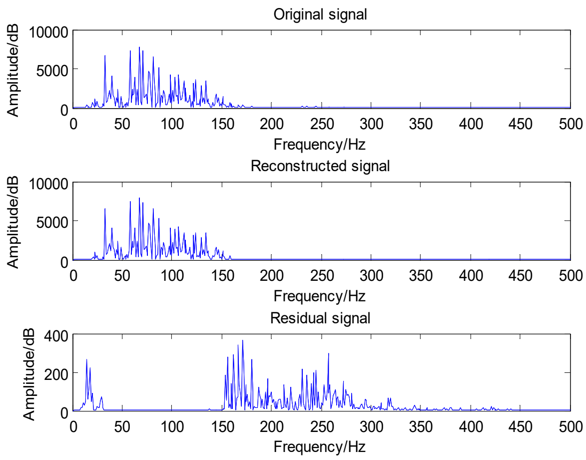

fig.6: Signal spectrum when r = 82

3.4 Comparison of original sEMG signal and reconstructed signal

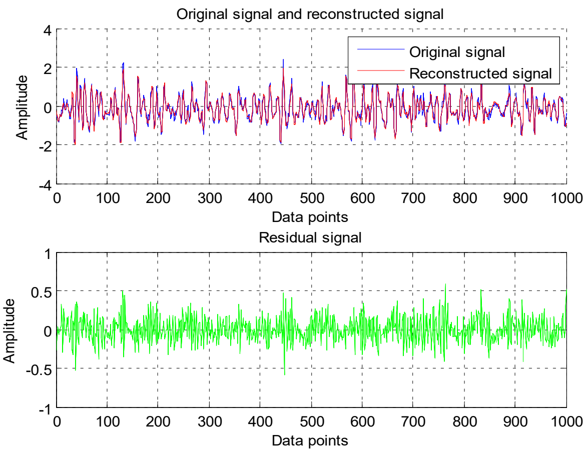

fig.7: Original signal and Reconstructed signal in time domain(r=82)

The original signal and reconstructed signal in time domain are both plot in the first figure when parameter r has a value of 82. As can clearly seen from the picture,two signals are essentially coincident with each other. And the amplitude of residual signal is far smaller than these two signals, which means that reconstructed signal retain as much useful power as possible in the region of interest.

4 Conclusions

SSA can effectively filter low frequency noise ranging from 0 to 50Hz and high frequency noise from 150 to 500Hz. When using a suitable value of parameter r to reconstruct signal, SSA can perfectly retain as much the signal components in the region of interest as possible. Also, compared with other traditional de-noising method, SSA is non-parametric and model-free, which can reduce complexity of the work and be less time-assuming. Therefore, SSA would have a bright future in de-noising sEMG signal .

References

[1] F.Romero, F.J. Alonso, J.Cubero, G.Galan-Marin, An automatic SSA-based de-noising and smoothing technique for surface electromyography signals, Biomedical Signal Processing and Control 18(2015) 317-324

[2] Juan Cheng, Xiang Chen, Minfen Shen, A Framework for Daily Activity Monitoring and Fall Detection Based on Surface Electromyography and Accelerometer Signals, IEEE Biomedical and health informatics, vol 17, No1, January 2013

[3] Delin Lu, Xingming Guo, Wavelet packet denosing algorithm for heart sound signal based on singular spectrum analysis, Journal of Vibration and Shock, Vol.32, No.18, 2013

[4] Delin Lu, Xingming Guo, Chaos Dynamics Analysis of Heart sound Based on Singular Spectrum Denoising, Chongqing University, April 2013

[5] Rongyi You, Zhong Chen, Higher order Singular Spectrum Analysis of EEG Based on Wavelet Transform, Journal of electronic measurement and instrument, Vol.19, No.2, April 2005

[6] G.Aschero, P.Gizdulich, Denoising of surface EMG with a modified Wiener filtering approach ,J.Electromyogr.Kinesiol.20(2)(2010) 366-373

[7] Yufeng Lu, Jafar Saniie, Singular spectrum analysis for trend extraction in ultrasonic backscattered echoes, 10.1109/ULTSYM . 2015 . 0440

[8] Delaram Jarchi, Louis Atallah, Guang-Zhong Yang, Transition Detection and Activity Classification from Wearable Sensors using Singular Spectrum Analysis, 2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks

[9] Konstantinos Eftaxias and Shirin Enshaeifar, Oana Geman, Samaneh Kouchaki, Detection of Parkinson's Tremor from EMG Signals:A Singular Spectrum Analysis Approach, 2015 IEEE 978-1-4799-8058-1/15

[10] Jian-ping Huang, Chuang Li, Guo-lei Li, Jin-qiang Huang, Zhen-chun Li, Chang-cheng Bu, Hou-hua Teng. Simultaneousseismic data de-noising and regularizationmethod based on singular spectrum analysis, Progress in Geophysics, 2014, 29(4): 1666-1671

[11] Chong Zhang, Xiaolin Yu, Yong Yang, Lei Xu, Mental Fatigue Electroencephalogram Signals Analysis Based on Singular System, Journal of Biomedical Engineering, Vol.31, No. 5, October 2014

[12] Angkoon Phinyomark, Frank Quaine, Sylvie Charbonnier, Christine Serviere, Franck Tarpin-Bernard, Yann Laurillau, EMG feature evaluation for improving myoelectric pattern recognition robustness, Expert Systems with Applications 40(2013) 4832-4840