香 港 大 學
THE UNIVERSITY OF HONG KONG

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DEPARTMENT OF ELECTRICAL & ELECTRONIC ENGINEERING

ELEC6081/MEDE4504 Biomedical Signals and Systems

Assignment Cover Sheet

Assignment No.:	**3**
Submission Date:	**24/11/2014**
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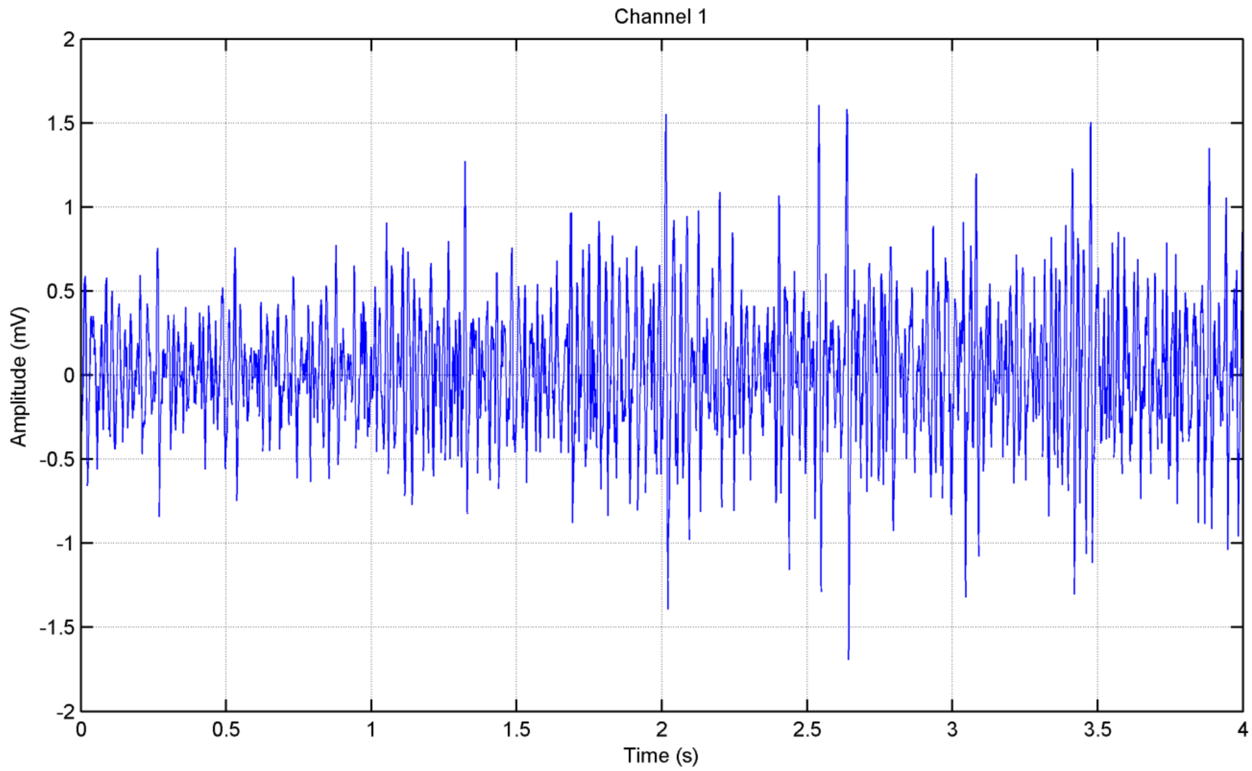
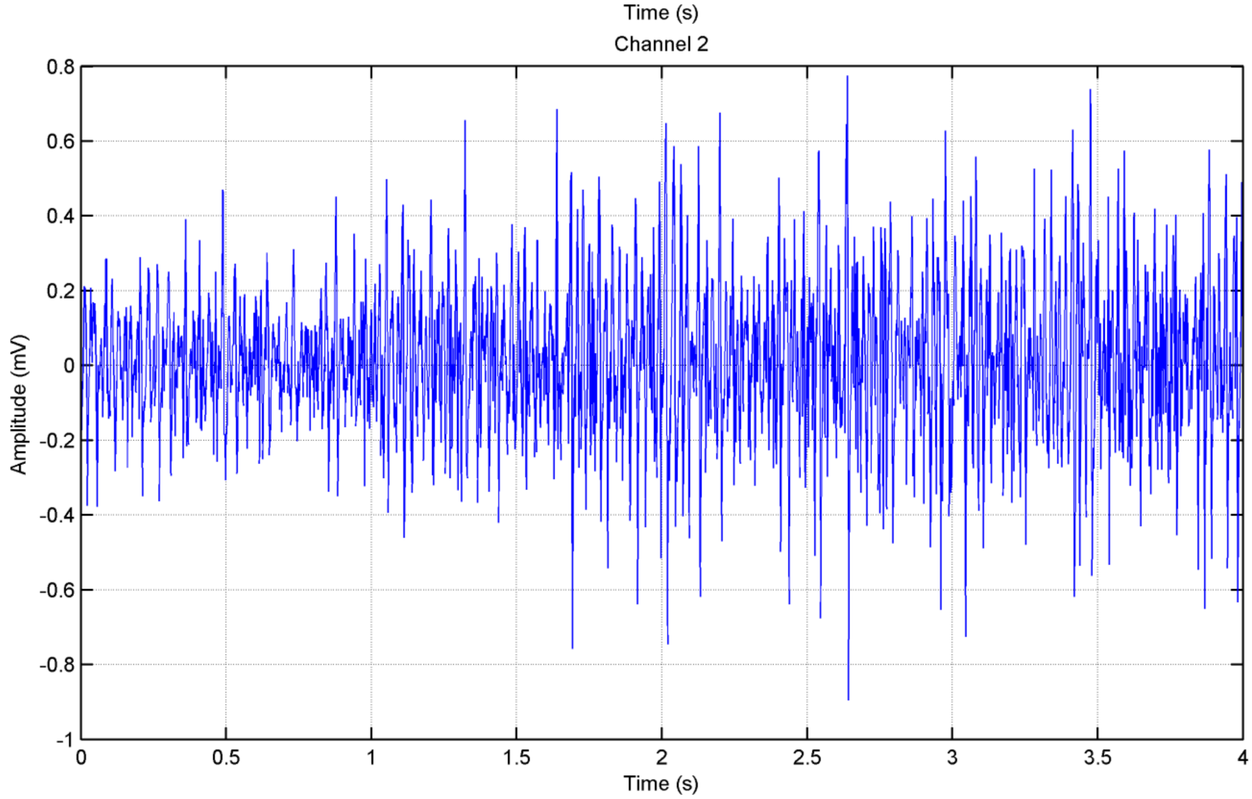
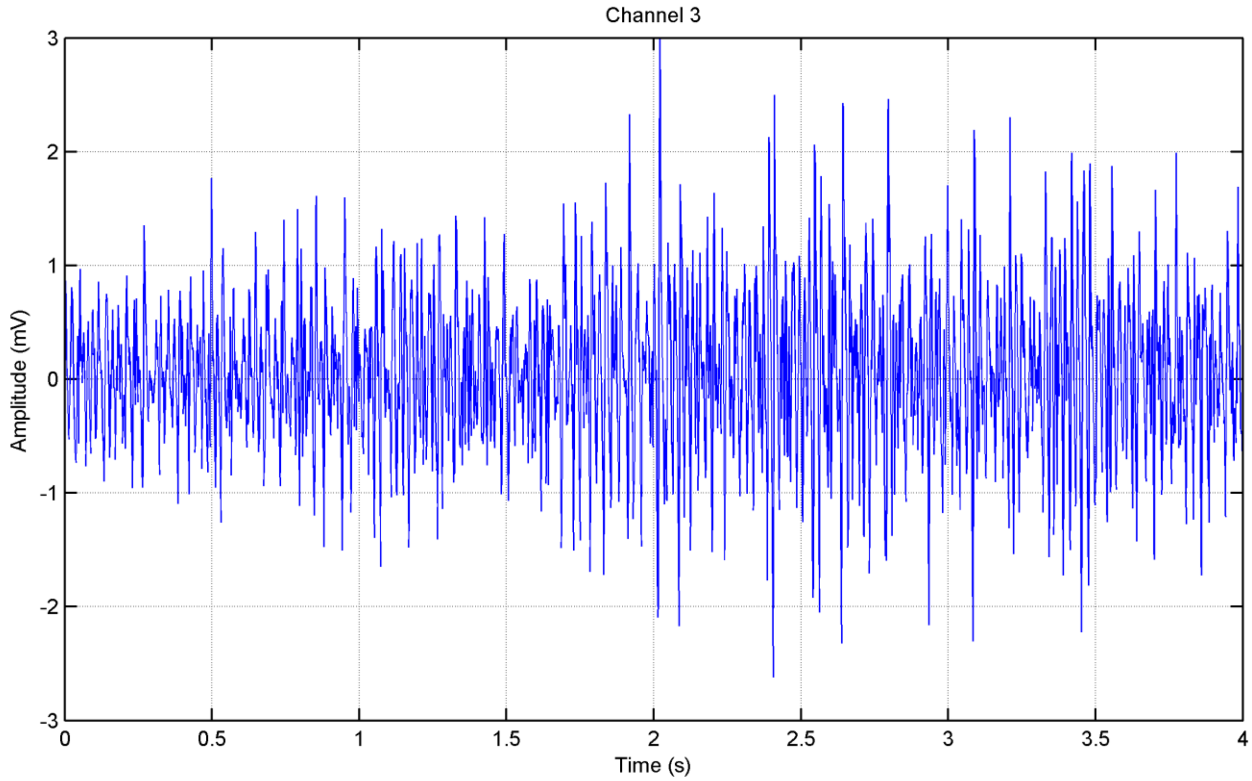
Date Received:	
Grade:	
Comments:	
Teaching Assistant:	

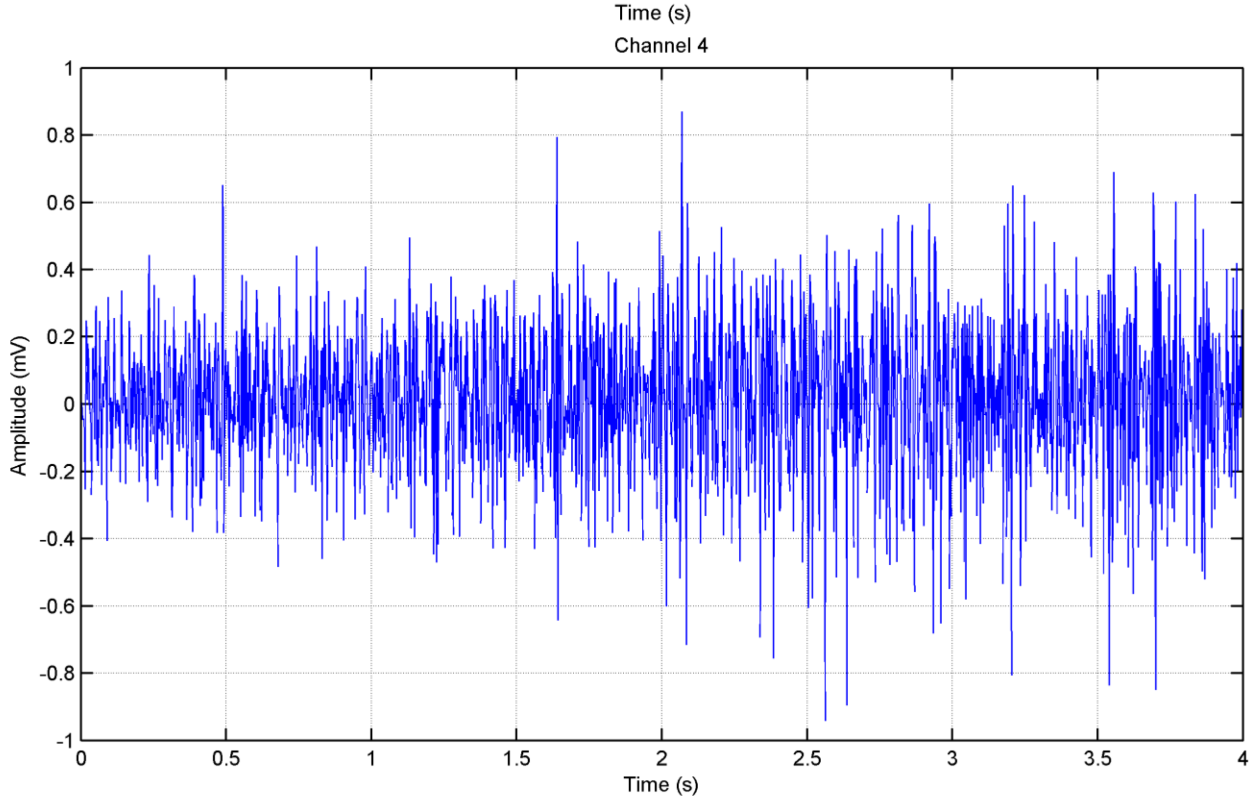
1. Correlation analysis of multichannel surface EMG (15 marks)

(i) Load 'assg3_emg.mat' and display the EMG signal of each channel separately. (3 marks)






Channel 3
Amplitude (mV)
Time (s)
3
2
1
0
-1
-2
-3
0
0.5
1
1.5
2
2.5
3
3.5
4


Channel 4
Amplitude (mV)
Time (s)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0
0.5
1
1.5
2
2.5
3
3.5
4

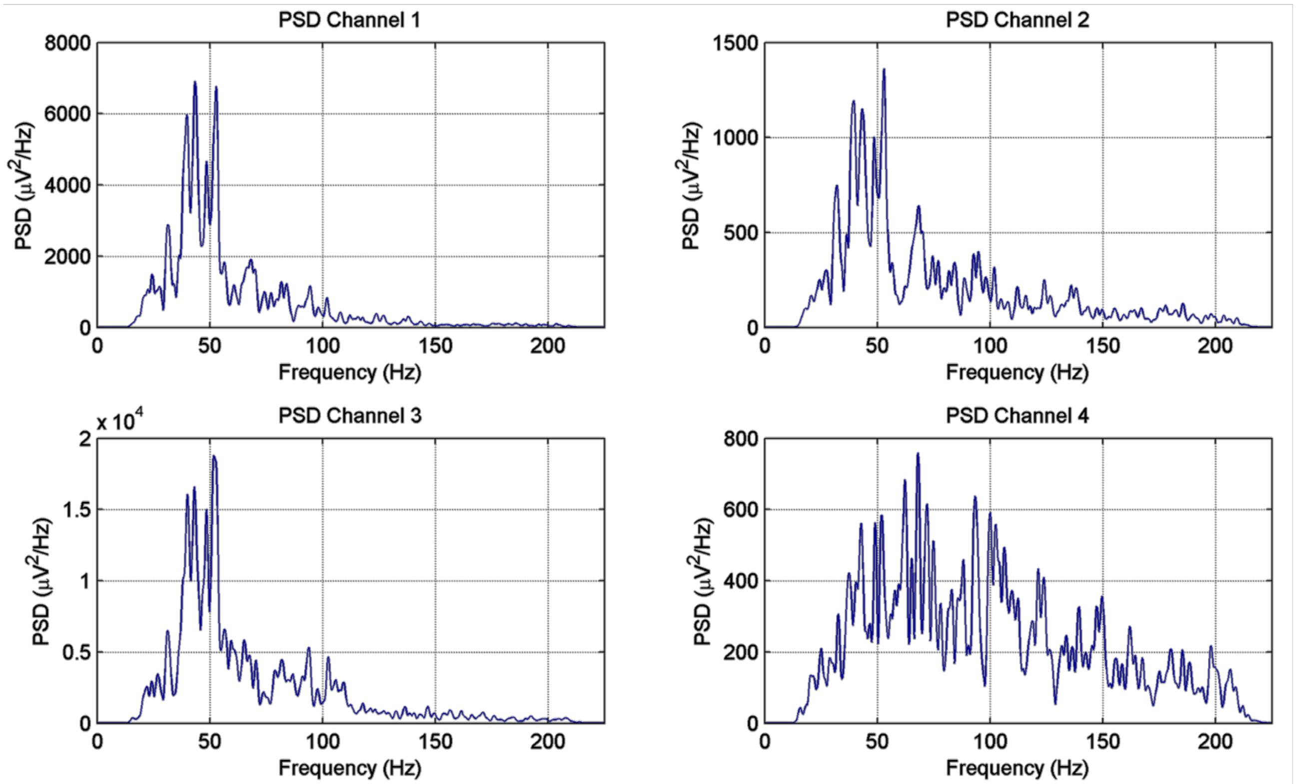
(ii) Compute the covariance, correlation and partial correlation between each pair of the EMG signal. Show the results clearly in tables. (6 marks)

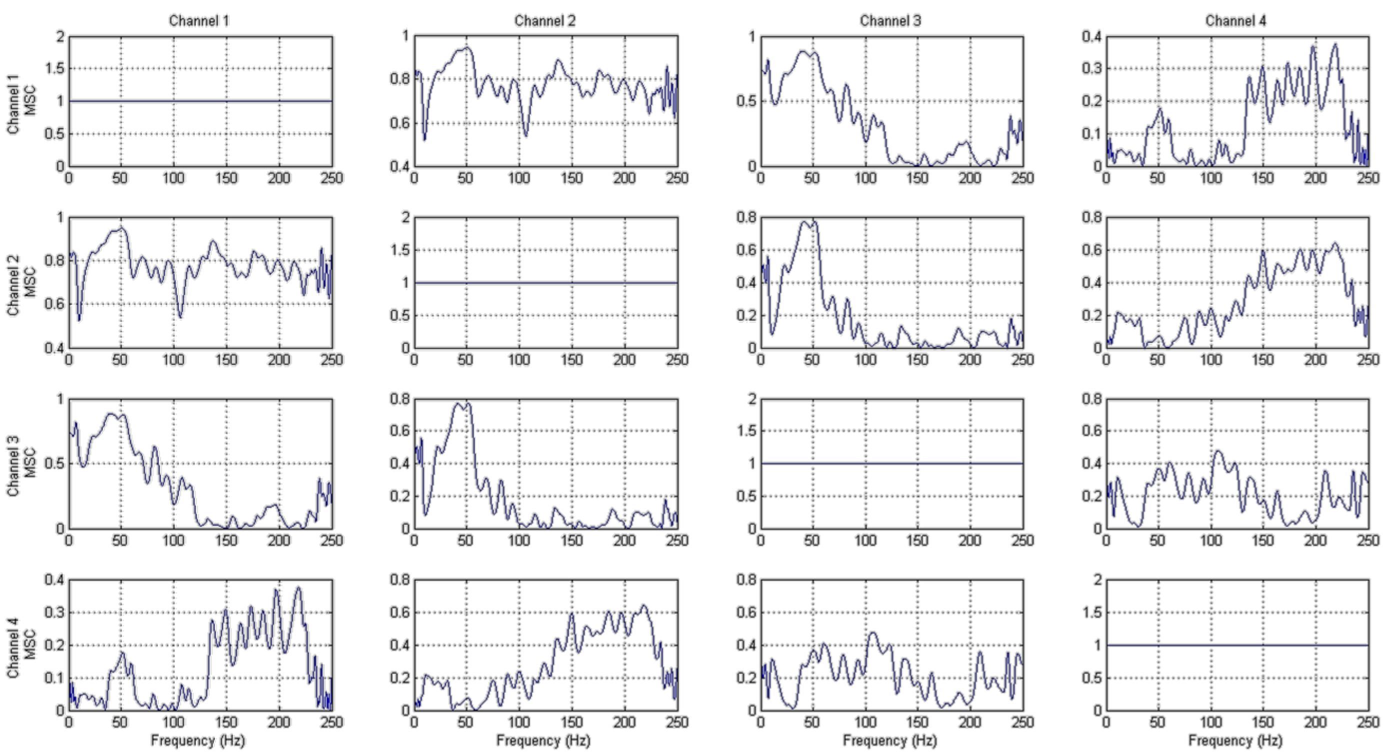
Covariance	Channel 1	Channel 2	Channel 3	Channel 4
Channel 1	0.1522	0.0717	-0.2079	-0.0052
Channel 2	0.0717	0.0424	-0.0785	0.0110
Channel 3	-0.2079	-0.0785	0.4792	0.0635
Channel 4	-0.0052	0.0110	0.0635	0.0000

Correlation	Channel 1	Channel 2	Channel 3	Channel 4
Channel 1	1.0000	0.8924	-0.7699	-0.0622
Channel 2	0.8924	1.0000	-0.5507	0.2485
Channel 3	-0.7699	-0.5507	1.0000	0.4265
Channel 4	-0.0622	0.2485	0.4265	1.0000

Partial correlation	Channel 1	Channel 2	Channel 3	Channel 4
Channel 1	1.0000	0.8569	-0.5256	-0.2784
Channel 2	0.8569	1.0000	0.1216	0.5556
Channel 3	-0.5256	0.1216	1.0000	0.4230
Channel 4	-0.2784	0.5556	0.4230	1.0000

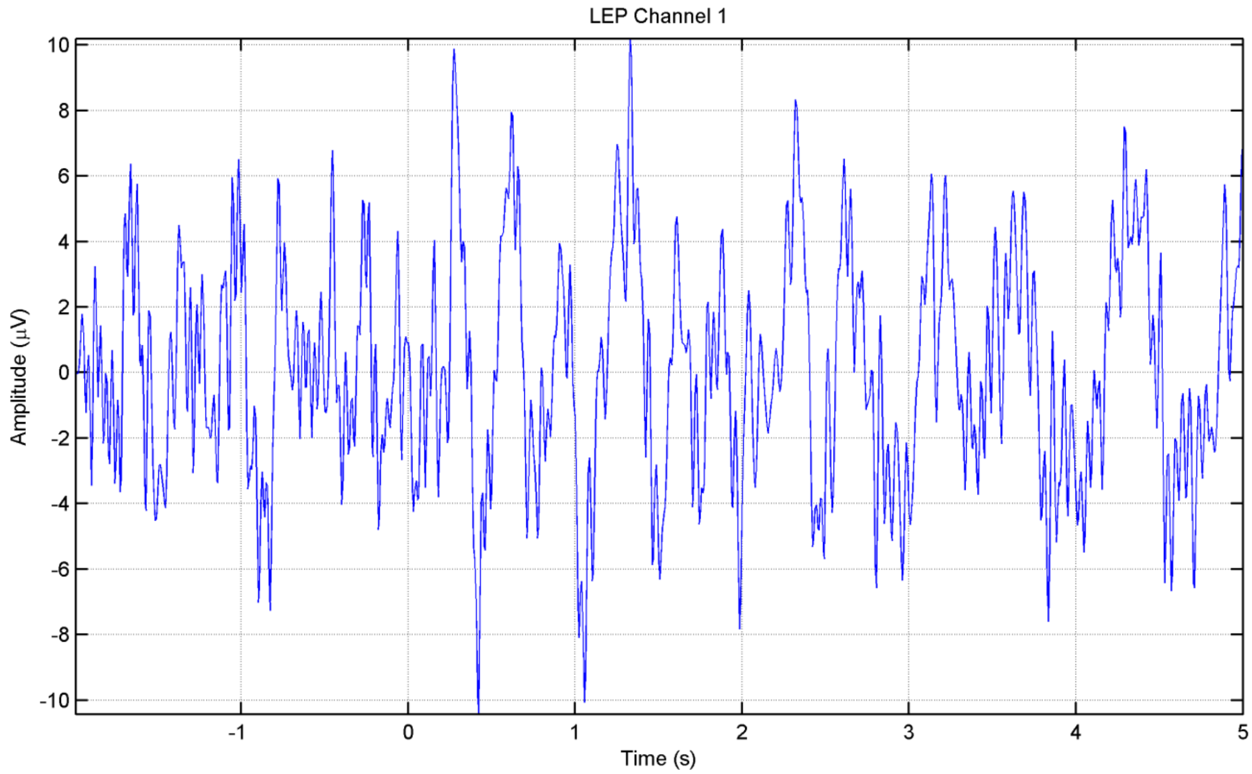
(iii) Estimate the PSD (using the Welch's method) of the EMG signal at each channel and calculate the magnitude squared coherence (MSC) between each pair of channels. In both the Welch's method and the coherence estimation, set the window length to be 100 and the overlapping ratio to be 50%. Plot all the results of PSD and MSC estimation. (6 marks)

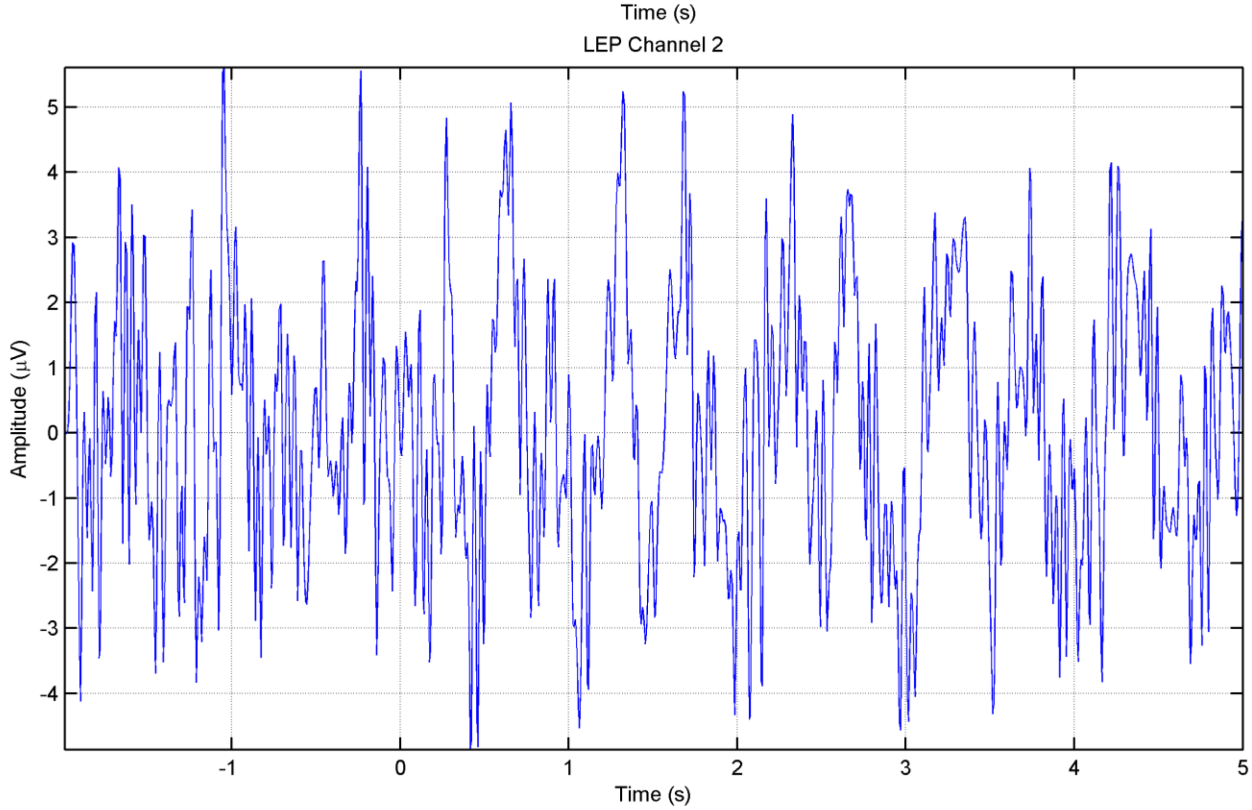

PSD Channel 1
PSD Channel 2
PSD Channel 3
PSD Channel 4
PSD (μV²/Hz)
Frequency (Hz)
x 10⁴

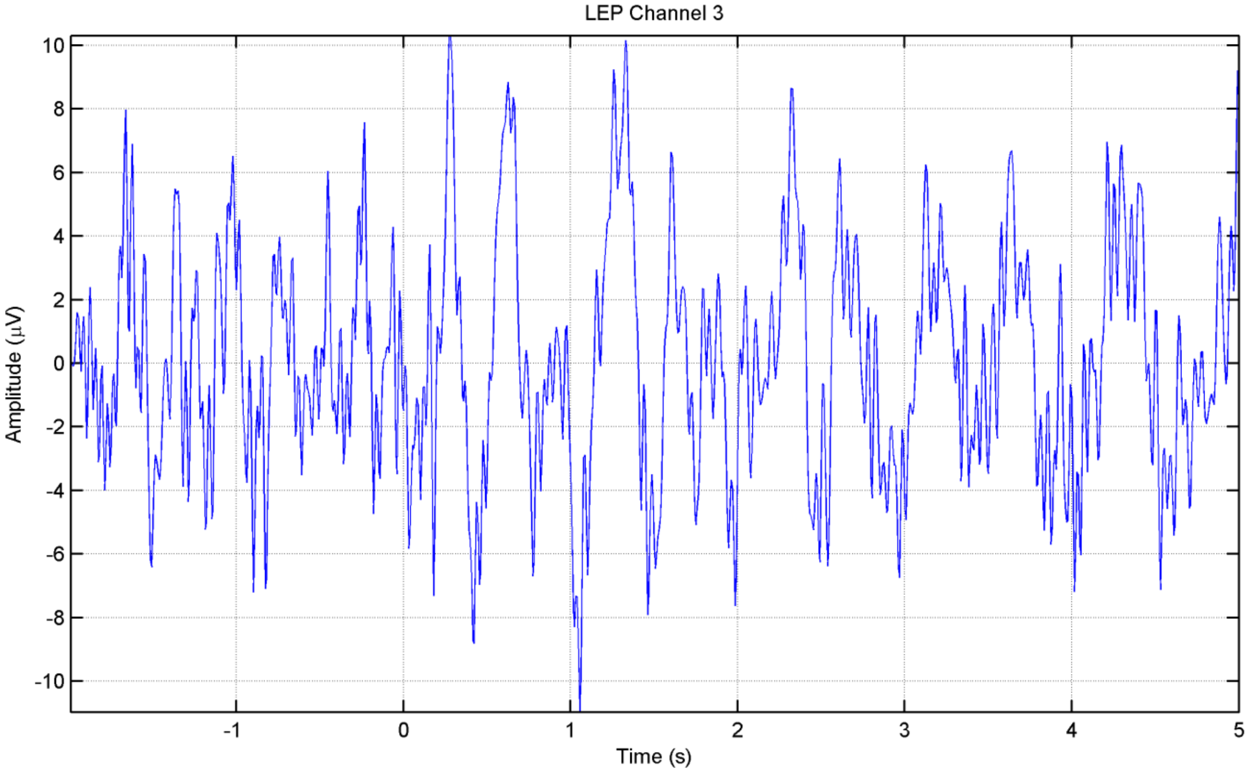

Channel 1
Channel 2
Channel 3
Channel 4
Channel 1 MSC
Channel 2 MSC
Channel 3 MSC
Channel 4 MSC
Frequency (Hz)

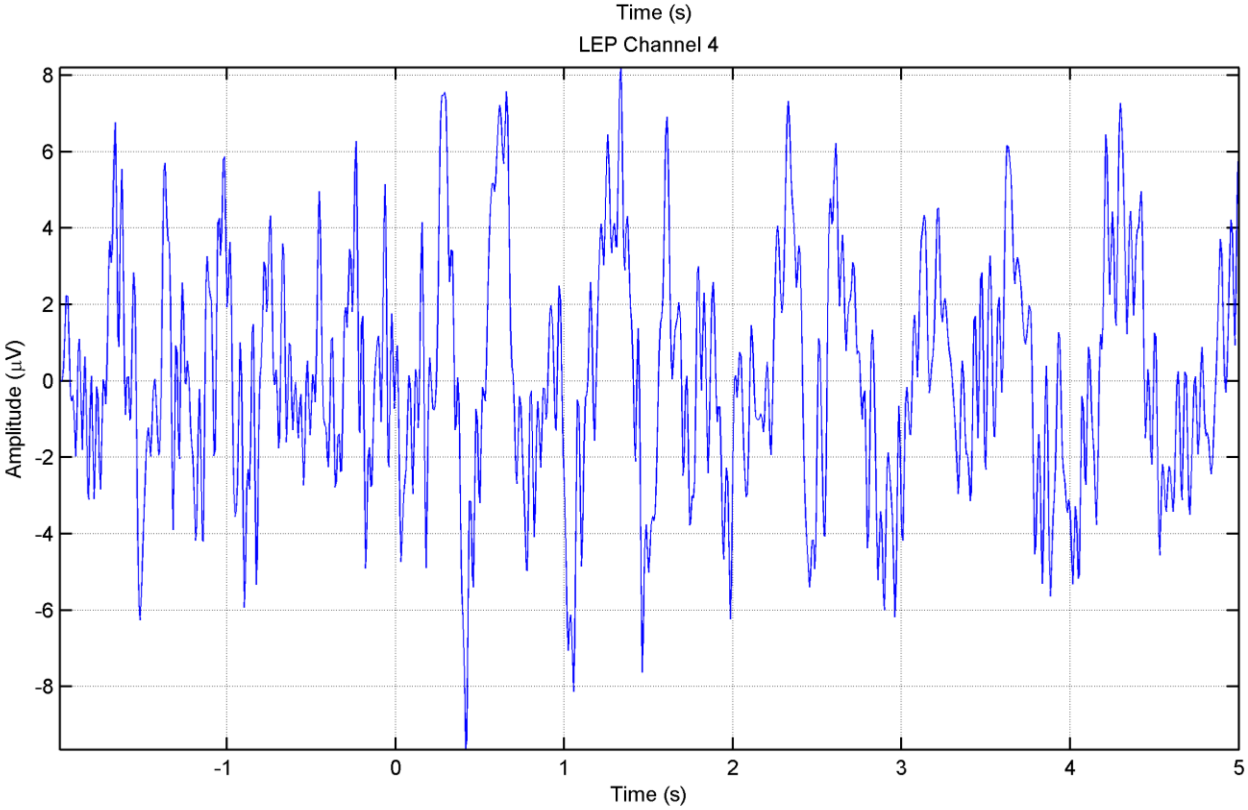
2. Principal component analysis of laser evoked potentials (15 marks)

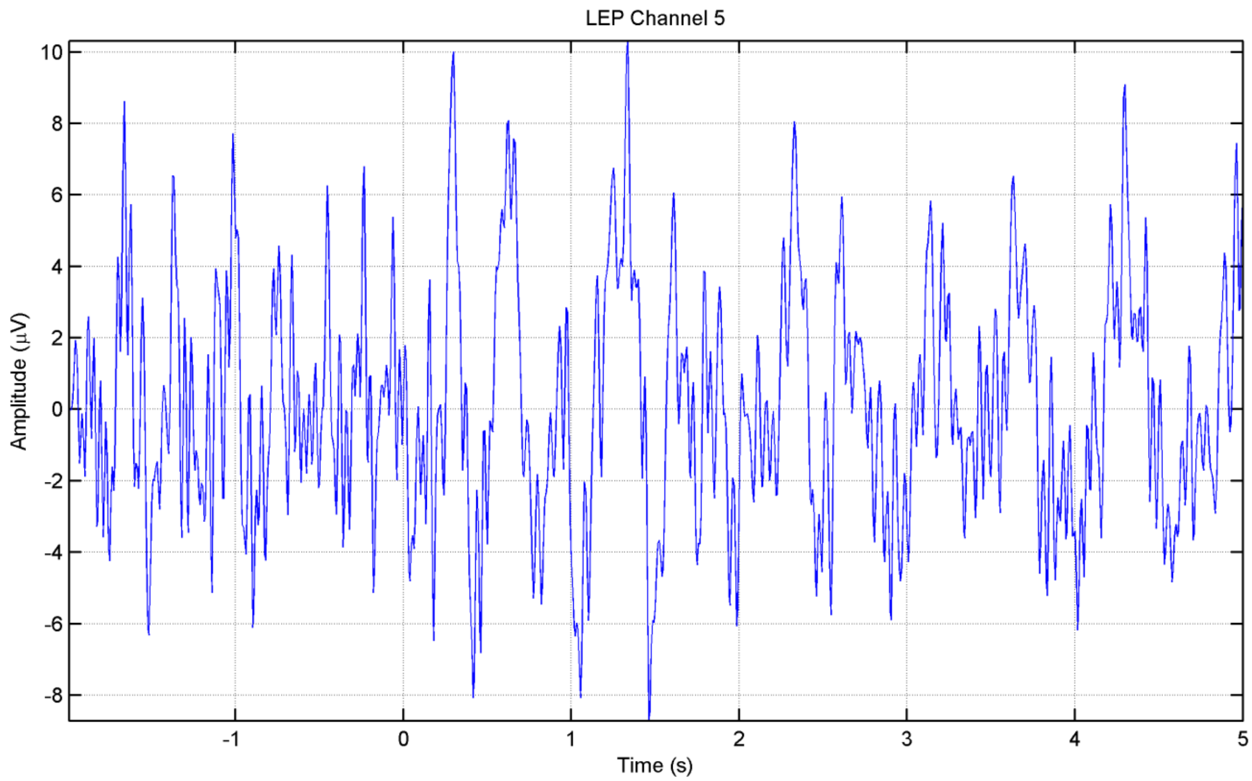
(i) Load 'assg3_lep.mat' and display the LEP signal of each channel separately. (3 marks)

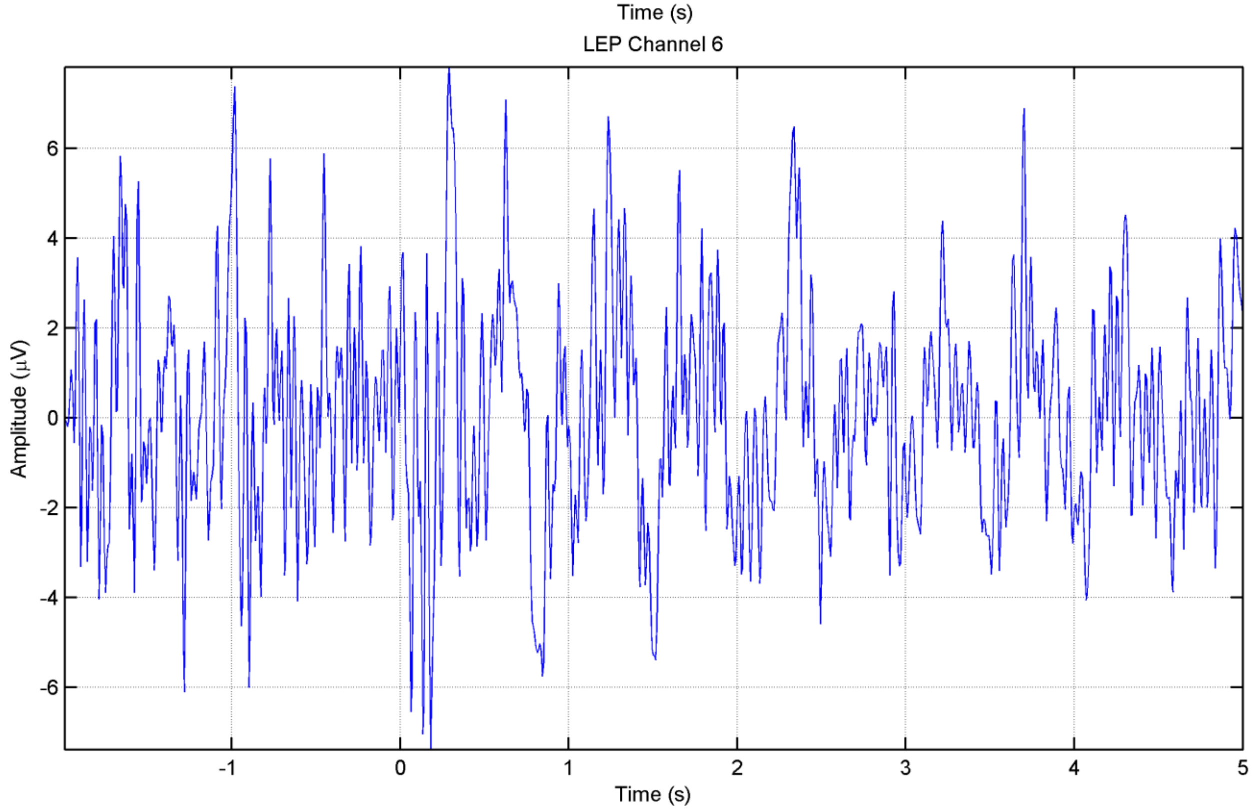


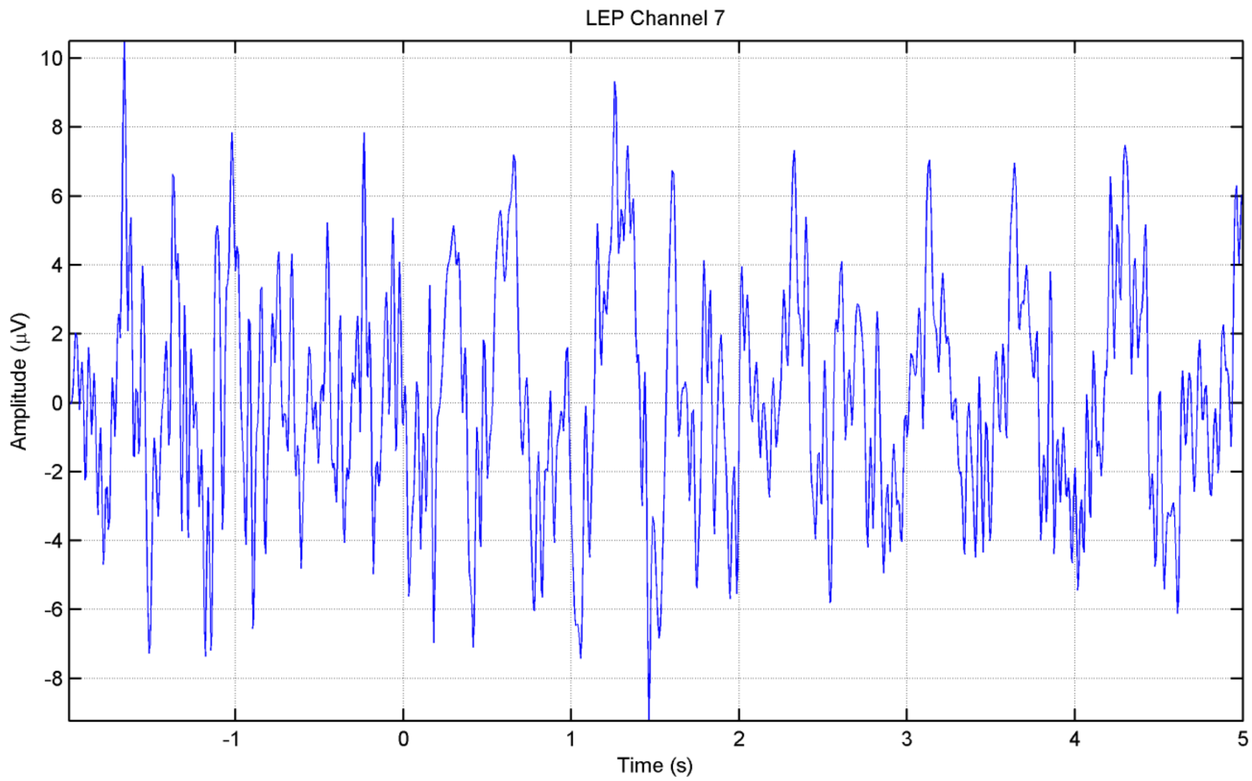



LEP Channel 3
Amplitude (μV)
10
8
6
4
2
0
-2
-4
-6
-8
-10
-1
0
1
2
3
4
5
Time (s)

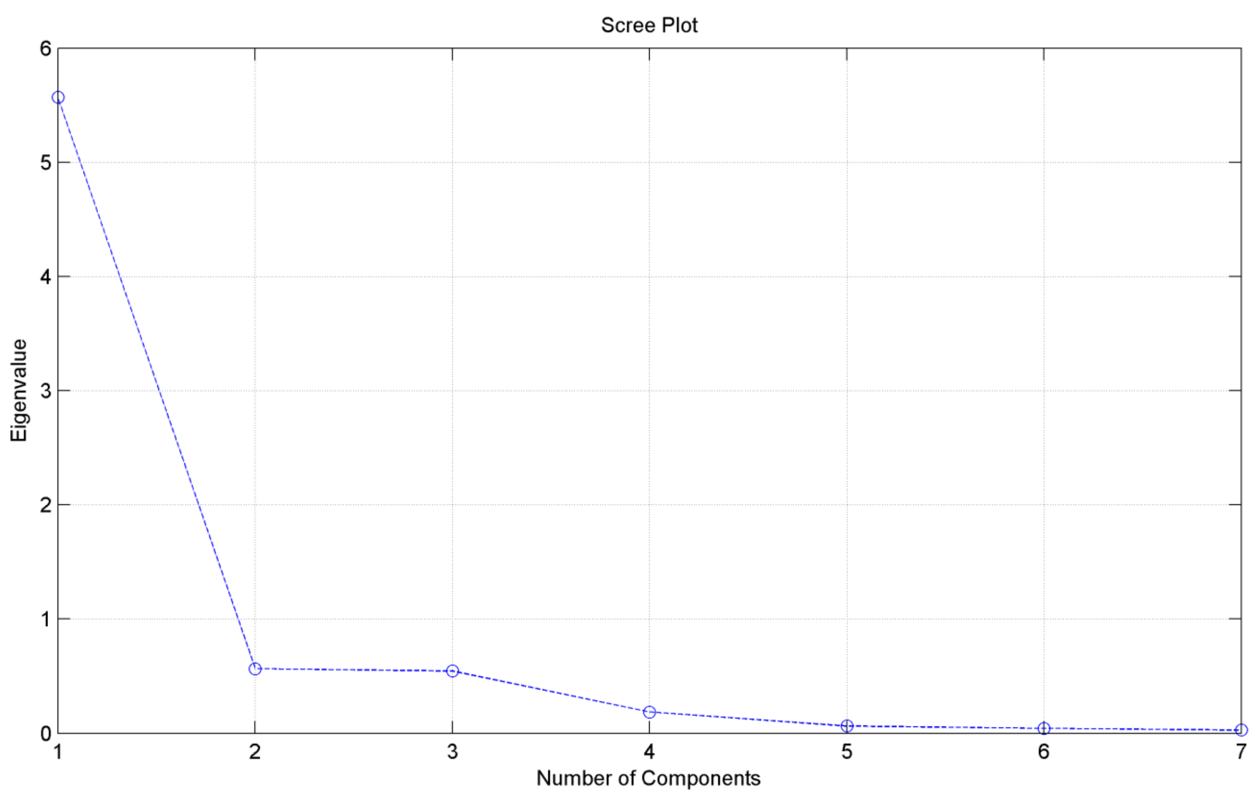

LEP Channel 4
Amplitude (μV)
8
6
4
2
0
-2
-4
-6
-8
-1
0
1
2
3
4
5
Time (s)


LEP Channel 5
Amplitude (μV)
Time (s)
10
8
6
4
2
0
-2
-4
-6
-8
-1
0
1
2
3
4
5

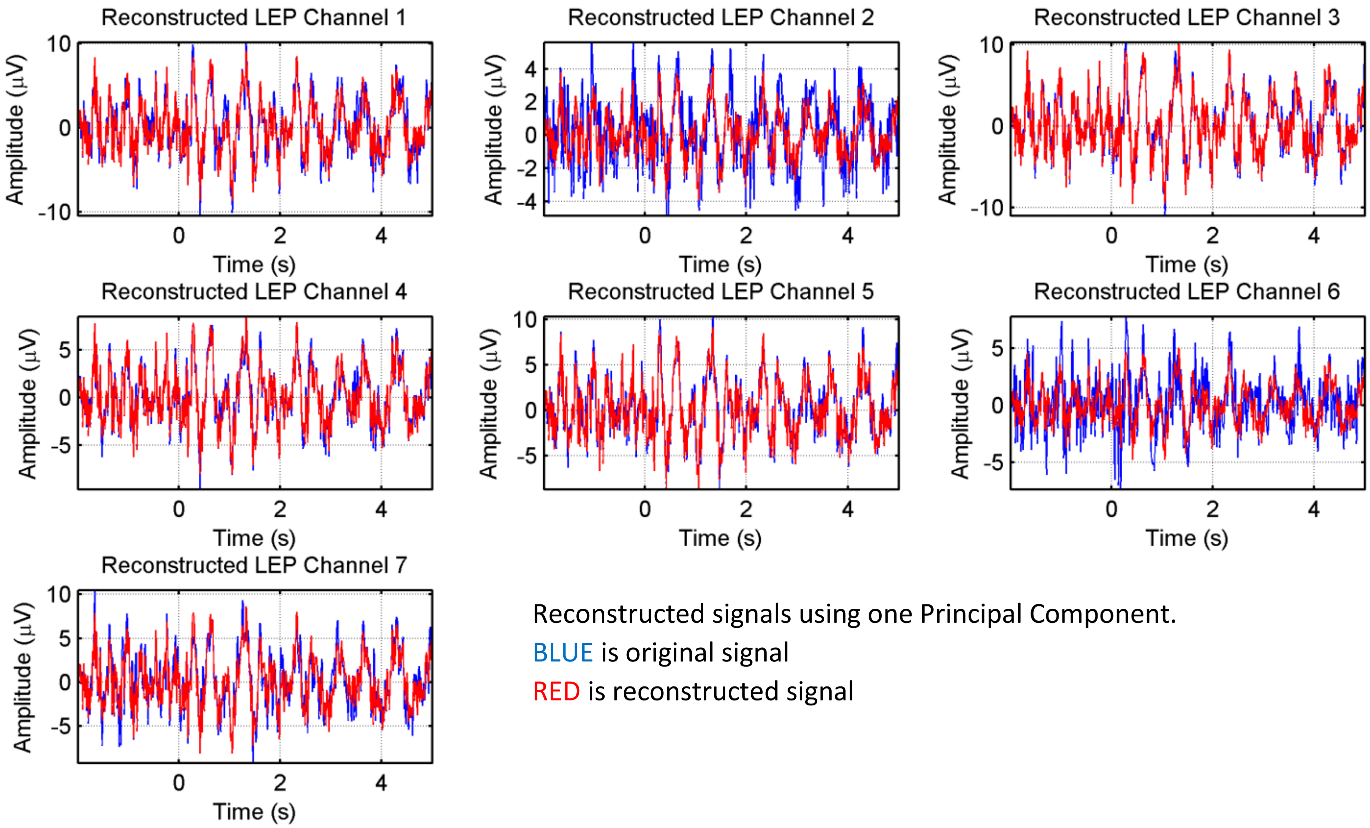

LEP Channel 6
Amplitude (μV)
Time (s)
6
4
2
0
-2
-4
-6
-1
0
1
2
3
4
5



(ii) Perform PCA on the LEP data. Show the scree plot. (3 marks)

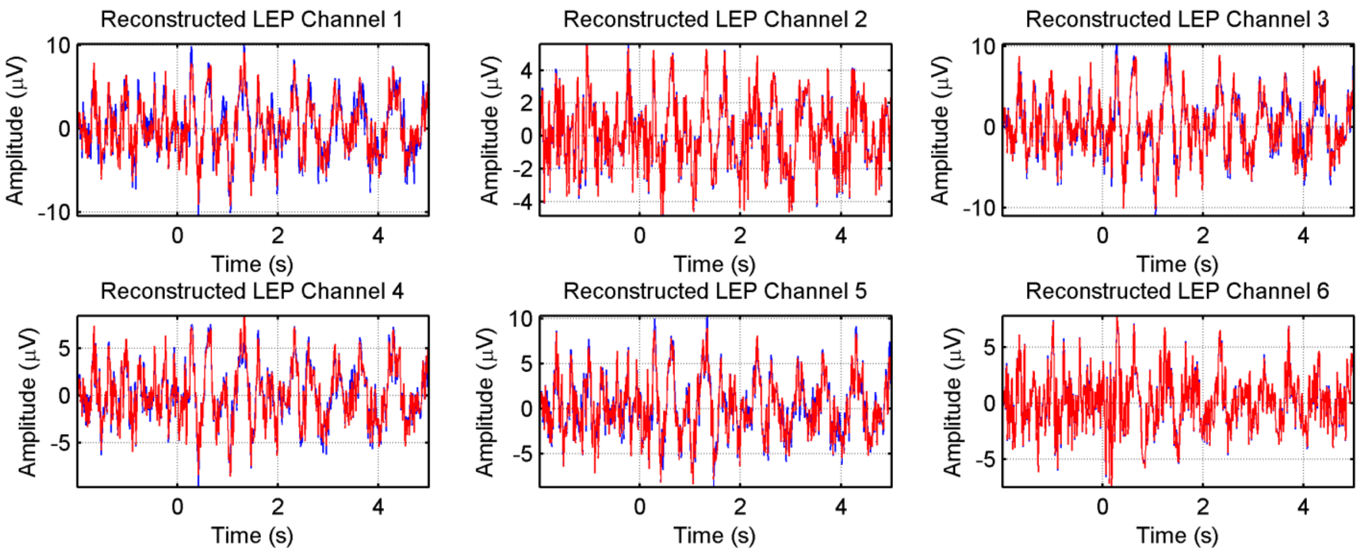


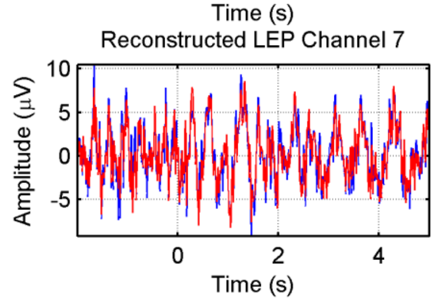
(iii) Use one principal component to reconstruct the LEP signal. Display the results (for comparison, the original signal should also be displayed as background). (3 marks)



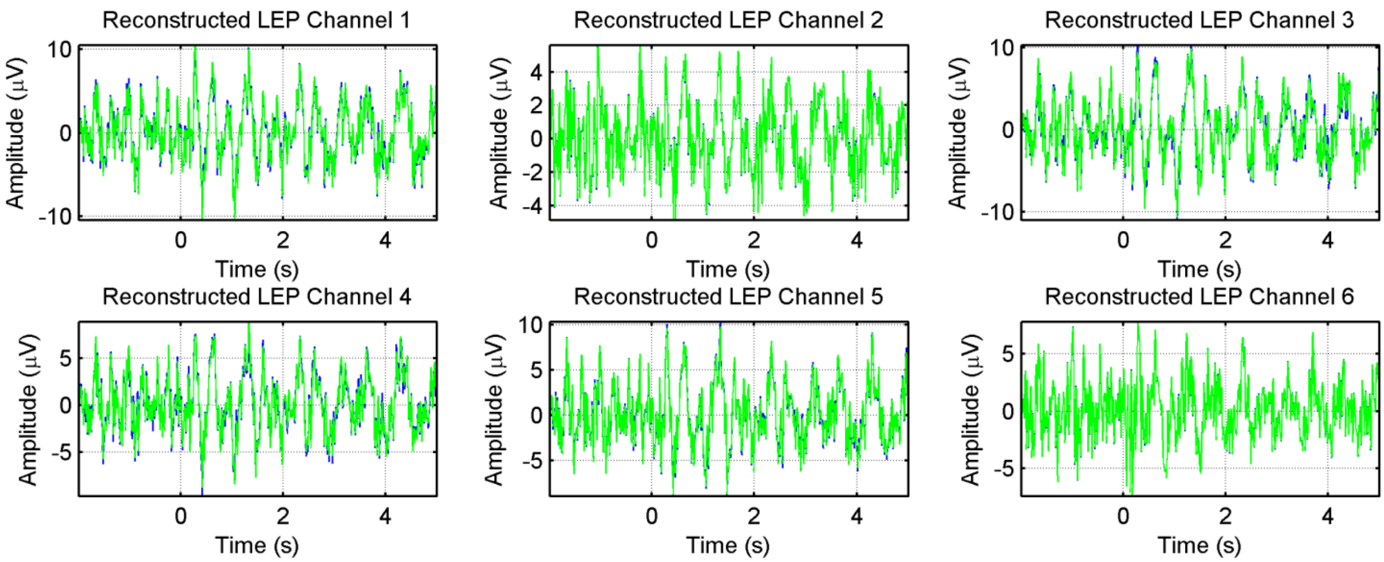
Reconstructed signals using one Principal Component.
BLUE is original signal
RED is reconstructed signal

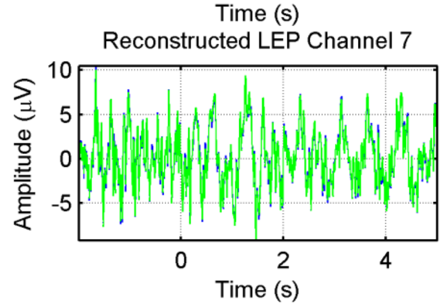
(iv) Use three and five principal components to reconstruct the LEP signal, respectively. Display the results (together with the original signal).



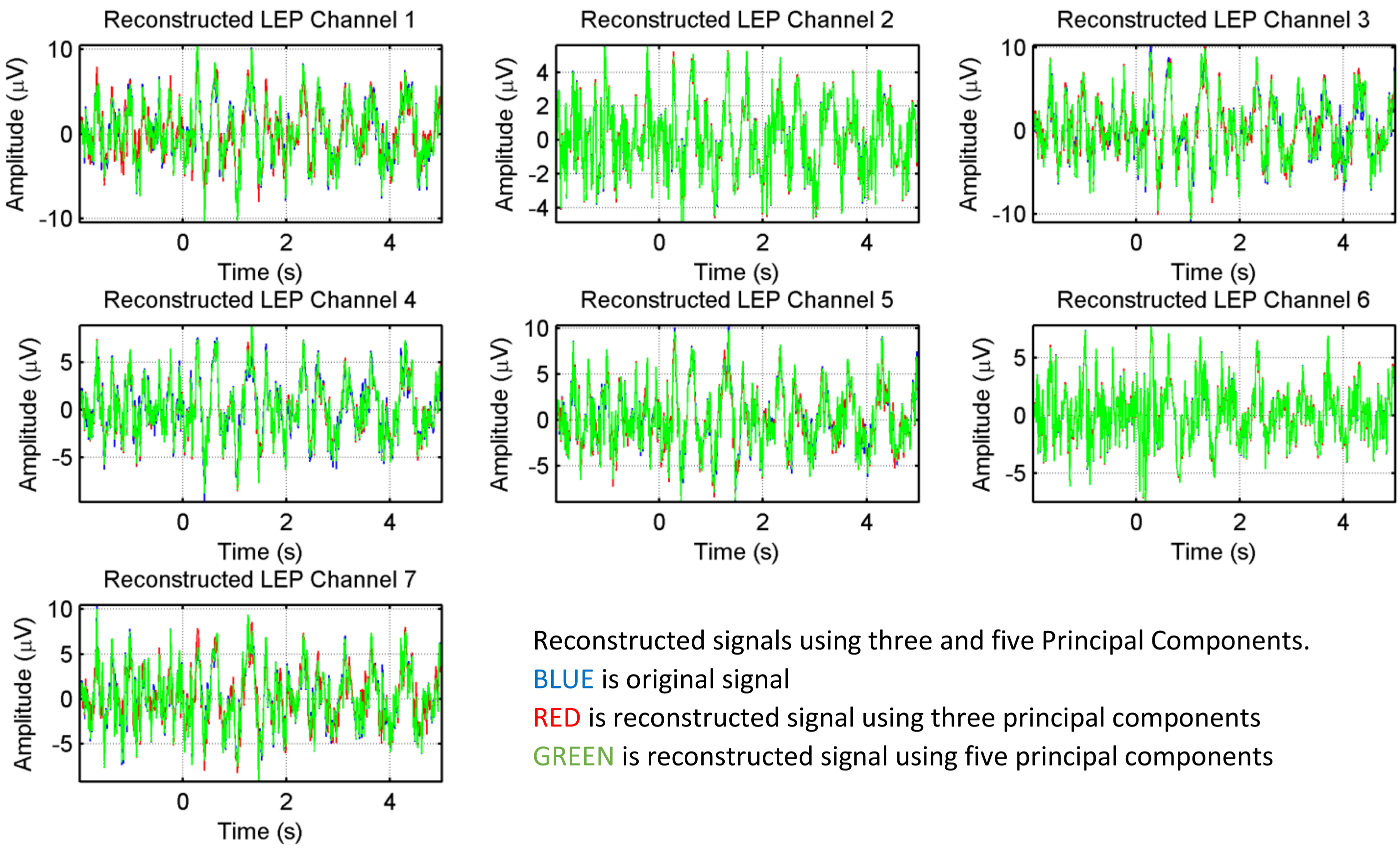


Reconstructed signals using three Principal Components.
BLUE is original signal
RED is reconstructed signal using three principal components





Reconstructed signals using five Principal Components.
BLUE is original signal
GREEN is reconstructed signal using five principal components



Reconstructed signals using three and five Principal Components.
BLUE is original signal
RED is reconstructed signal using three principal components
GREEN is reconstructed signal using five principal components

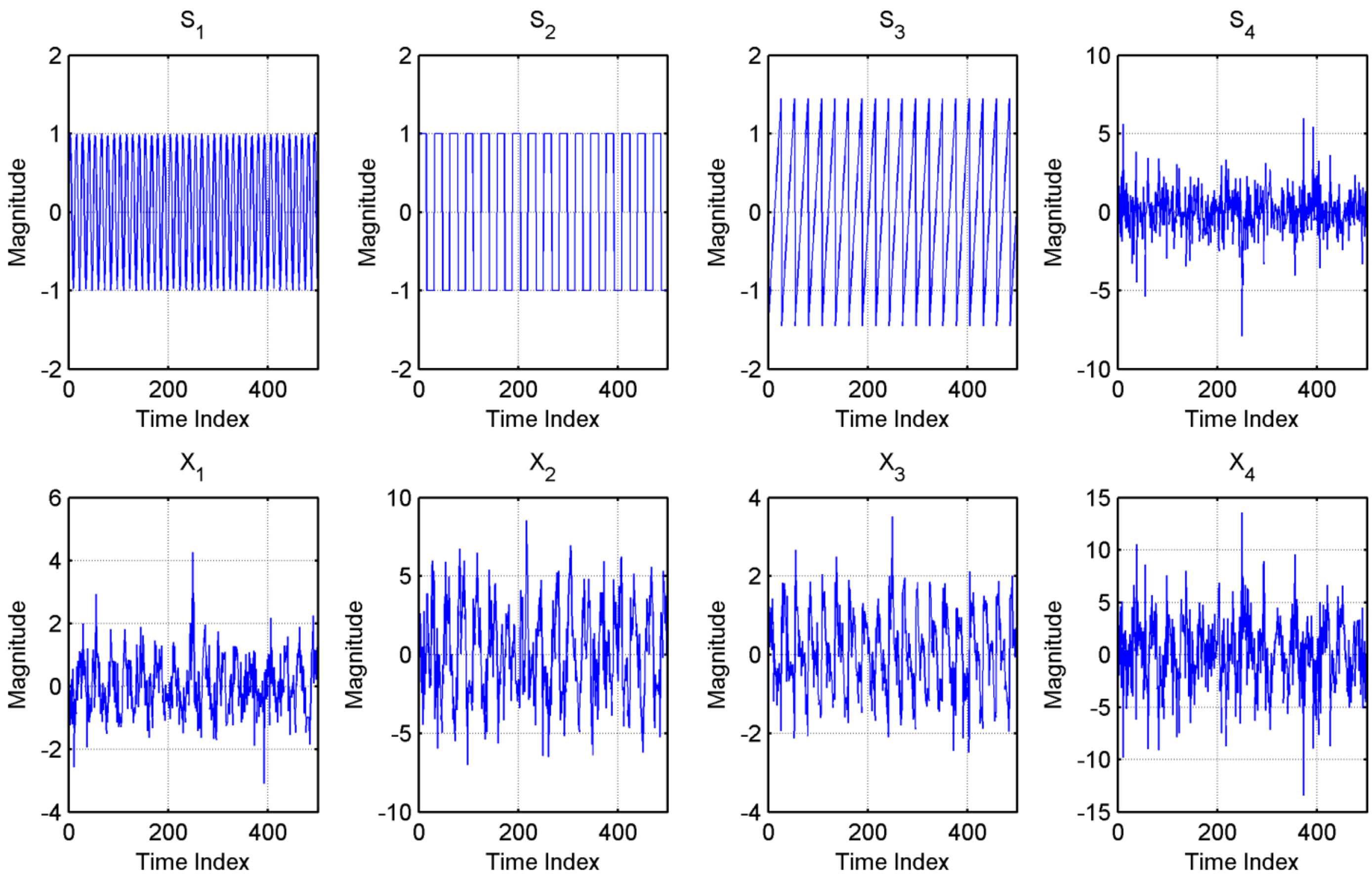
Describe the difference between reconstructed results using different number of principal components, and suggest the best number of components (less than the total number of components) that should be used for reconstructing the signal. (6 marks)

As we increase the number of principal components towards the total number of components, the reconstructed signal tends closer and closer towards the original signal. We can see a significant shift in the closeness towards the original signal when we go from one to two components. From five components however there is less and less variance between the original signal and the reconstructed signal.

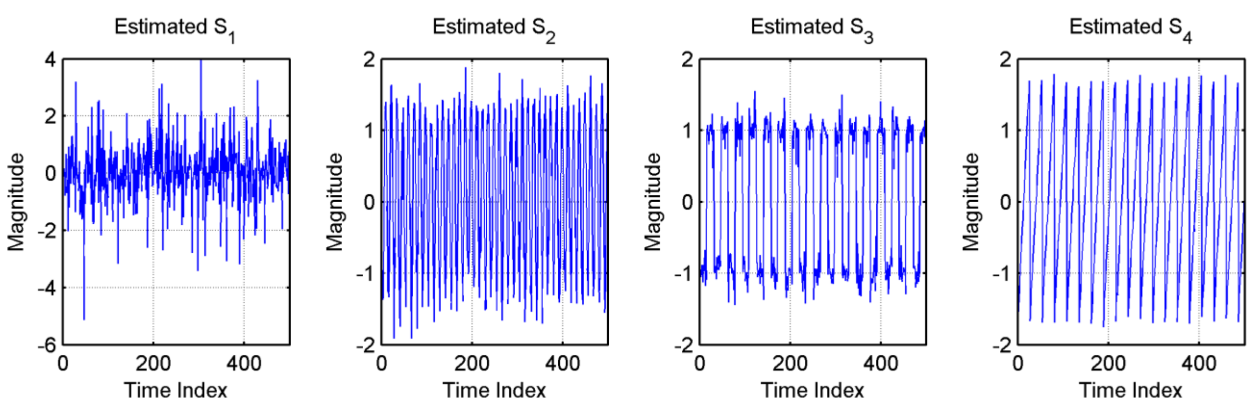
The best number of components (less than total number of components) that should be used for reconstructing the signal is four since from the fifth component onwards the scree plot is almost flat meaning each successive component accounts for less and less towards the total variance.

3. Independent Component Analysis (10 marks)

(i) In the ICA example of the handout 3, change the 2nd independent component funny curve to a square wave as: S(2,:) = square([1:N]/5); % square wave and set the mixing matrix A as: A = [-0.3 -0.6 -0.3 -0.4; 1.6 -2.0 -1.2 1.0;... -0.4 0.0 -1.0 -0.3; 0.2 1.7 0.4 -2.0]; Plot all original independent components and the mixed signal. (3 marks)

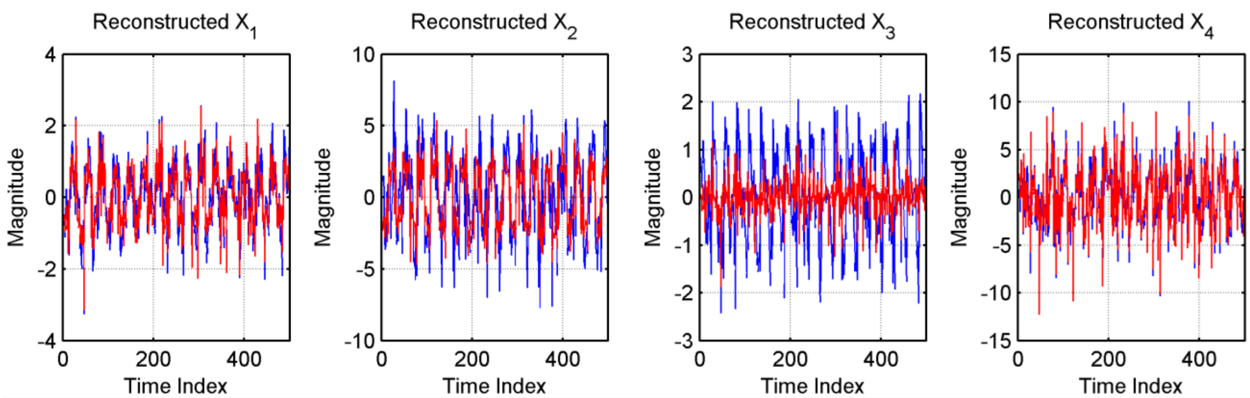


(ii) Use fastica to implement ICA on the mixed signal. Plot all estimated independent components. (3 marks)



(iii) Remove two independent components corresponding to the impulsive noise and the sine wave and reconstruct the mixed signal using the remaining two independent components. Display the reconstructed mixed signal (for comparison, the original signal should also be displayed as background). (4 marks)

Reconstructed signal in RED, with impulsive noise and sine wave removed (1st and 2nd Independent Components). Original signal in BLUE.



4. Pattern classification (40 marks)

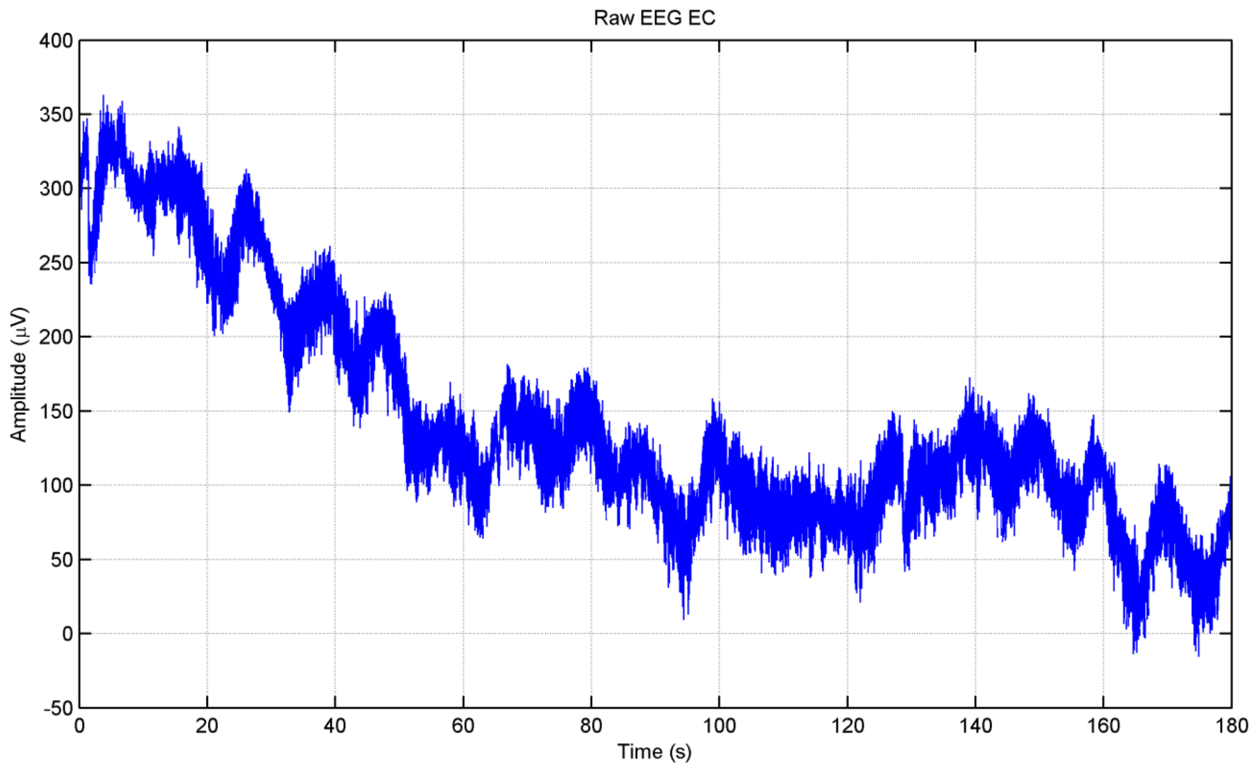
Load assg3_eeg_classification.mat. The requirement of this question is to classify unknown_trials (field data without class labels) with eeg_ec and eeg_eo (available raw EEG data).

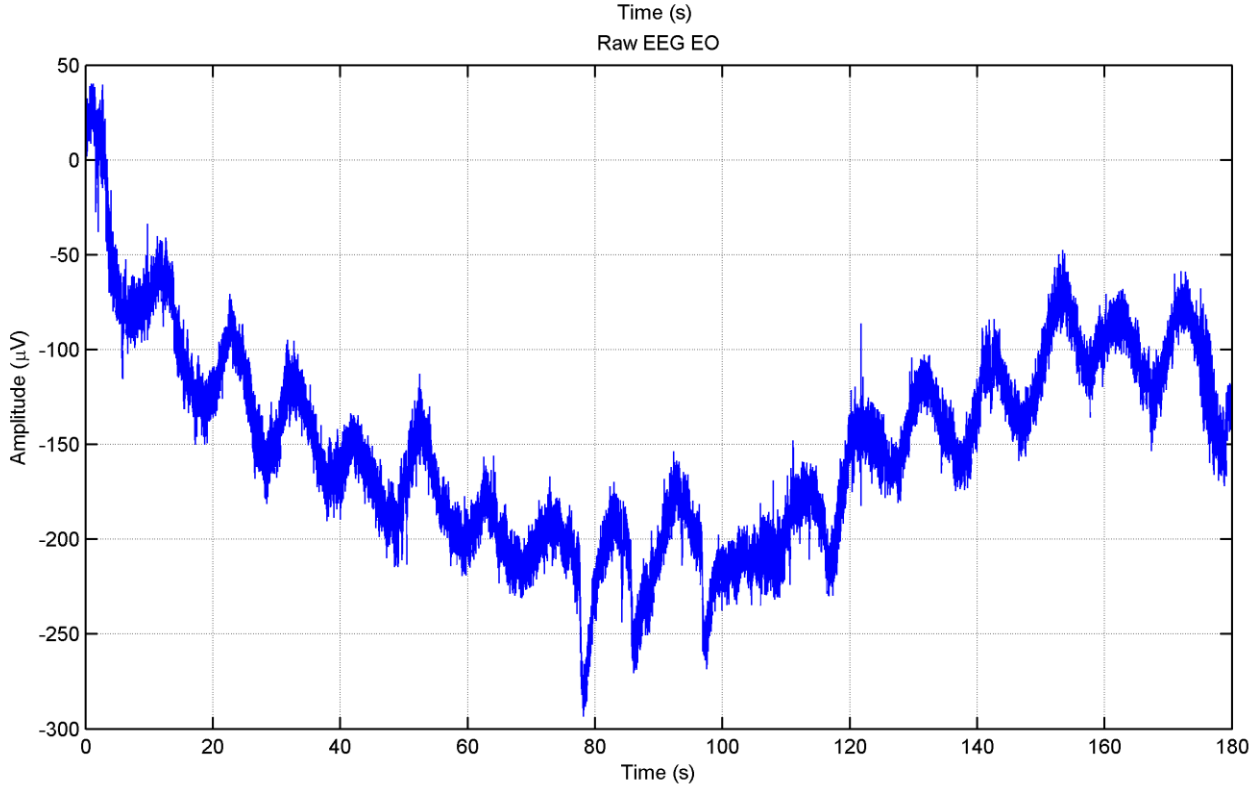
- **(i)** **Propose pre-processing, feature extraction, and other procedures on raw EEG data eeg_ec and eeg_eo. Use Matlab function classify and 10-fold cross validation to test the generalization performance of a discriminant analysis classifier with available data eeg_ec and eeg_eo (which must be appropriately pre-processed; see Note 1 below). List the detailed data analysis steps and the generalization performance (in terms of accuracy, sensitivity, and specificity, where "positive" is eyes-open and "negative" is eyes-closed).**

Steps

1. Pre-Processing (Bandpass filtering 8-12 Hz)
2. Feature Selection – use alpha power since large variance between eyes closed and eyes open
3. Process data to generate multiple trials, framing data into 1 second window
4. Feature extraction – calculate alpha power for each 1 second window
5. Outlier removal based on 3 standard deviation from median (absolute distance calculation)
6. Classify use LDA and SVM
7. Cross Validation

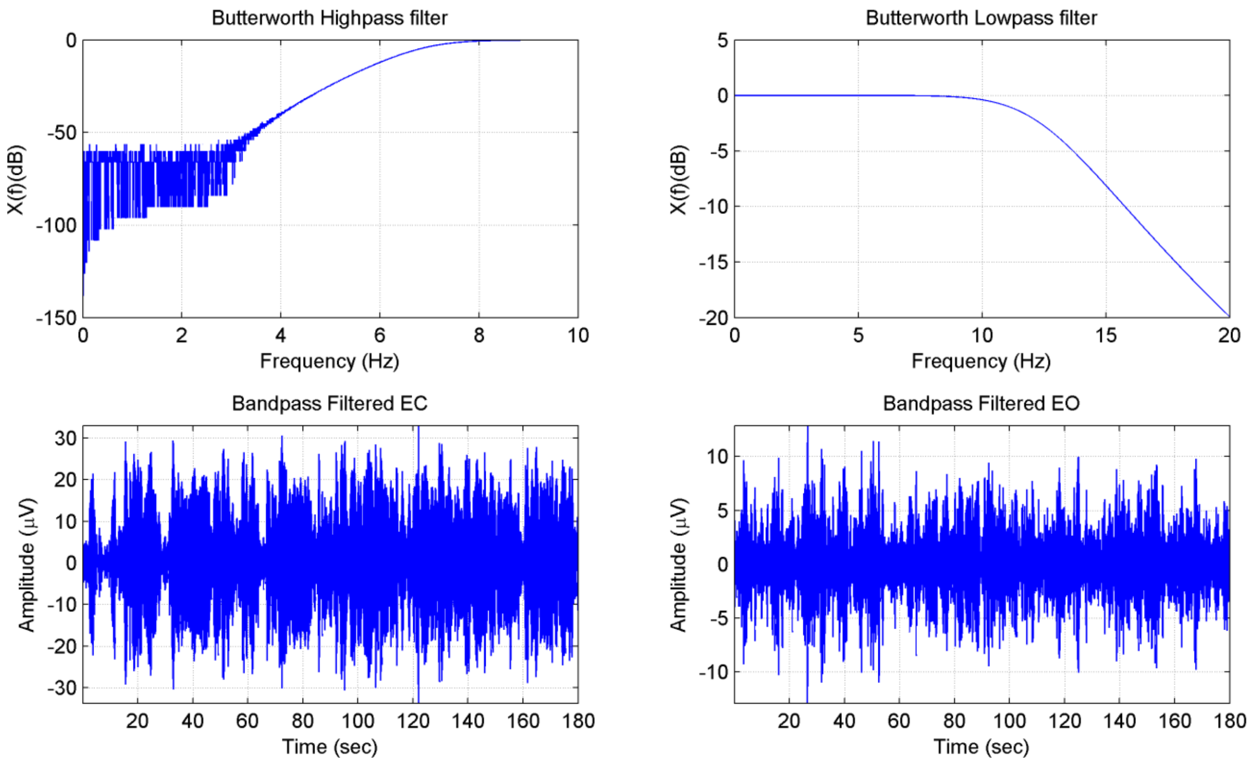
Raw EEG Signals





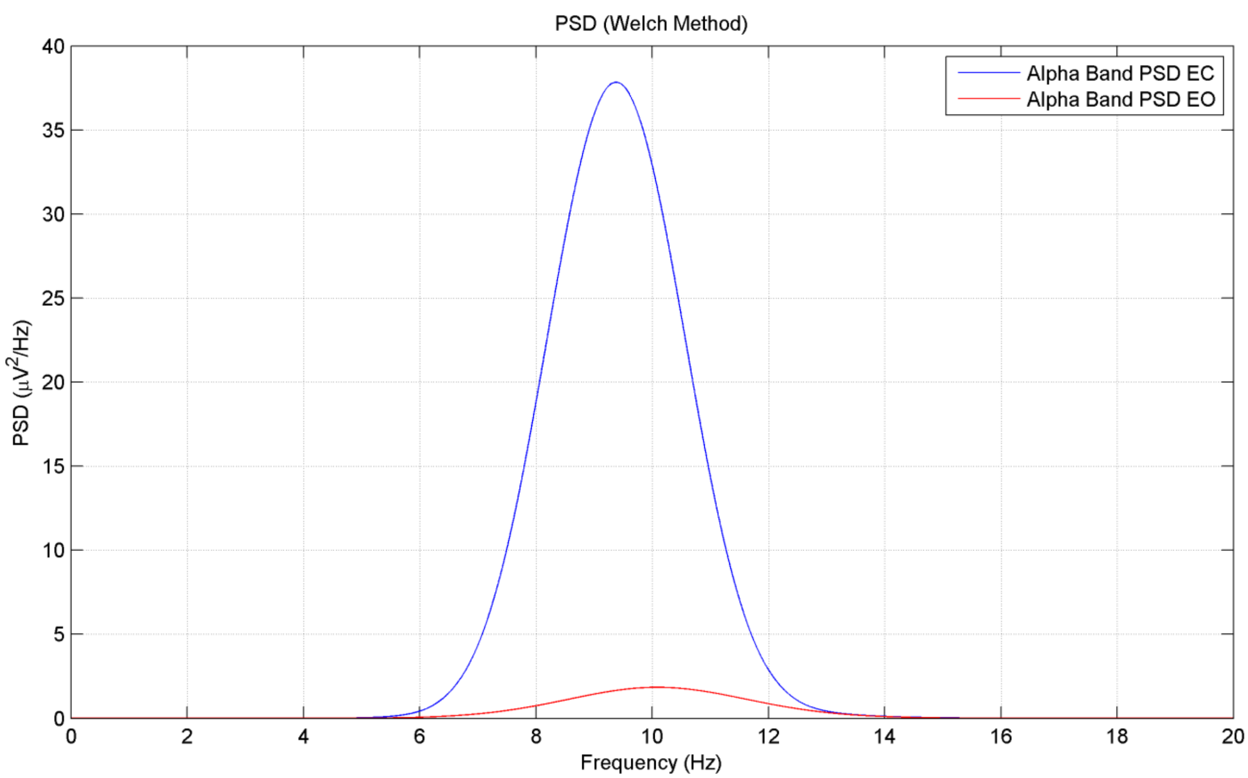
Pre-Processing

Alpha band, butterworth bandpass filtering was used (8-12Hz).

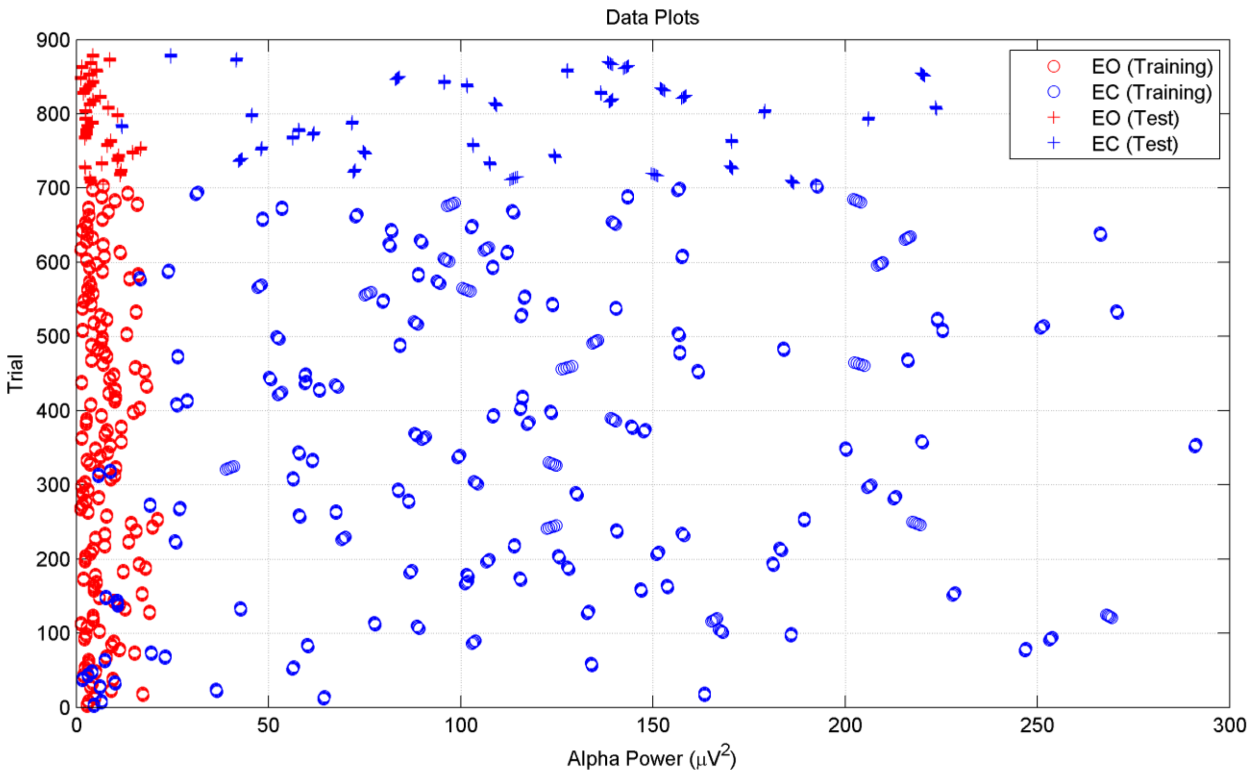


Feature Selection

Alpha power was used as feature selection, since we can see that there is max variance in PSD between eyes closed and eyes open in the alpha band.



Plot of training data and test data with eyes open and eyes closed. Alpha power is the feature used.



Generalization Performance using 10-fold cross validation with LDA

Average Accuracy	0.8733
Average Specificity	1.0000
Average Sensitivity	0.7727

Generalization Performance using 10-fold cross validation with SVM

Average Accuracy	0.9295
Average Specificity	1.0000
Average Sensitivity	0.7727

(ii) Further, use Matlab function classify to train a classifier with data eeg_ec and eeg_eo and to predict the class labels of all trials in unknown_trials (field data without class labels). List each processing step (from pre- processing, feature extraction, to classification) and the associated parameters. Submit the predicted class labels as a separate file (see Note 2 below).

Processing Steps

1. Pre-Processing (Bandpass filtering 8-12 Hz)
2. Feature Selection – use alpha power since large variance between eyes closed and eyes open
3. Feature extraction – calculate alpha power for each 1 second window
4. Classify use SVM

Plot of training data, test data and unknown trials with eyes open and eyes closed. Alpha power is the feature used.