The commentary of HW 3 (P300 Speller)

Question (1):

Part (1):

For describing the purpose of this paper leisurely I must explain the BCI systems (which could be used to control external devices such as robots, virtual environments, or spelling devices) types which are:

SSVEP (steady-state visual evoked potentials): This technique is used widely with electroencephalographic research regarding vision and attention. They are natural responses to visual stimulation at specific frequencies.

SCP (slow cortical potentials): sensitive to long-term fluctuations.

Oscillations in Alpha and Beta bands

P300-ERP(event-related-potential)

Motor-imagery: BCI systems based on oscillations use mostly motor imagery. This type of BCI is mainly used for cursor control on computer screens, for navigation of wheelchairs or in virtual environments.

In this paper despite of other previous papers, they have used p300 event-related-potential method (instead of motor imagery or etc.). They have used p300 ERP in order to build a speller using real-time EEG and by finding target and non-target choices.

Part (2): In the present study, they have used two paradigms to implement the P300 speller:

The row/column (RC) speller: highlights multiple characters at once and

The single character (SC) speller: flashes each character individually.

A total of 81 subjects used the RC speller, 38 subjects the SC speller and 19 subjects tested both versions. Subjects must be focused on the monitor and look at the word the want to spell. They get EEG from g.USB amplifier with sampling frequency of 256 Hz.

Firstly, they were said to spell “WATER” for system training and

then, after using LDA model they must spell “LUCAS”.

When a highlight appears (in an array or a row and a column)

for 15 times, the system determines its decision and shows it on the monitor.

Part (3):

The key feature we could use for comparing target and non-target is the peak of p300. The P300-based BCI systems use the effect that an unlikely event induces the P300 component in the EEG.

They have used a buffer to get the real-time EEG after showing each array or RC for 800 ms and with a tag of the image number.

After using bandpass filter (0.5-30 Hz) and down sampling, we are able to use LDA in order to find a line which could separate our data perfectly.

Part (4):

When we analyzed the data, whereas for one case the accuracy of SC was 100, the mean accuracy of RC was much more than SC.

Paper says that the RC paradigm is superior to the SC paradigm and 89% of the 81 RC subjects were able to spell with accuracy 80–100%.

An interesting finding was that the system was more accurate for people who slept less the previous night but sex, education, working duration, and cigarette and coffee consumption were not statistically related to differences in accuracy and didn’t have significant influence on the results.

A higher P300 amplitude and more reliable control was expected with the SC flasher because it is more unlikely that the target character appears and their results suggested that the SC paradigm produced larger P300 responses.

And, the current results strongly suggest the P300-based BCI is superior to a motor imagery system, if the goal is to quickly achieve highly accurate and reliable results. (By comparing with another experiment).

These are the final results for both methods

Classification accuracy in %	Row-column speller: percentage of sessions ($N=81$)	Single character speller: percentage in sessions ($N=38$)
100	72.8	55.3
80–100	88.9	76.3
60–79	6.2	10.6
40–59	3.7	7.9
20–39	0.0	2.6
0–19	1.2	2.6
Mean accuracy of all subjects	91.0	82.0
Spelling time [s]	28.8	54
Mean accuracy of subjects who participated in RC and SC ($N=19$)	85.3	77.9

Theoretical Neuroscience Computation

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part2

question 1

For each subject we have a struct witch containing the informations of test and train experiment. in each experiment we have a matrix including 11 rows. first row is corresponding to time in millisecond, second to ninth rows are corresponding to EEG signals from 8 different electrodes. tenth row contains the number of row or column or character when they shined and eleventh shows which columns of tenth row are target. when a column in eleventh row is 1, the corresponding column in tenth shows that this character is target.

question 2

To understand that which methods were used for each subject we refer to tenth row of train or test matrices of each one and check if tenth rows have elements larger than 12, then SC method were used for correspond subject. but if all elements of tenth row is lower than or equal to 12 RC method were used.

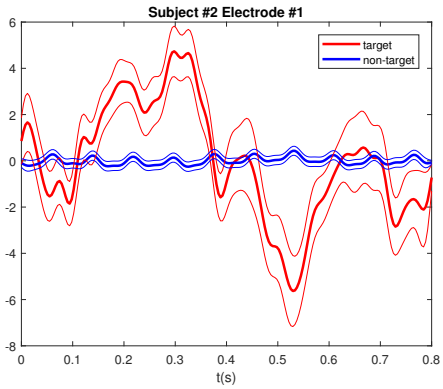
subject number	method
sub1	SC
sub2	SC
sub3	RC
sub4	RC
sub5	RC
sub6	RC
sub7	RC
sub8	RC
sub9	RC
sub10	RC

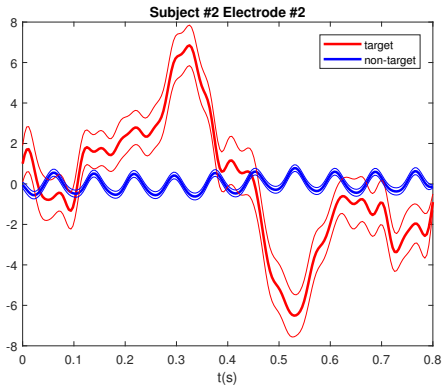
question 3 & 4

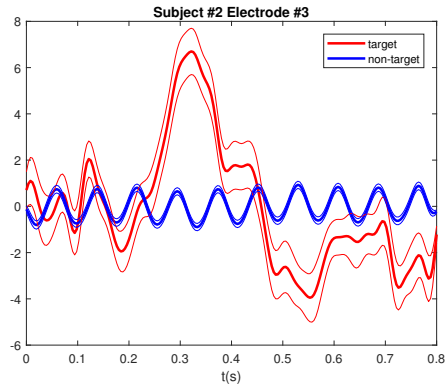
codes were inserted to the file.

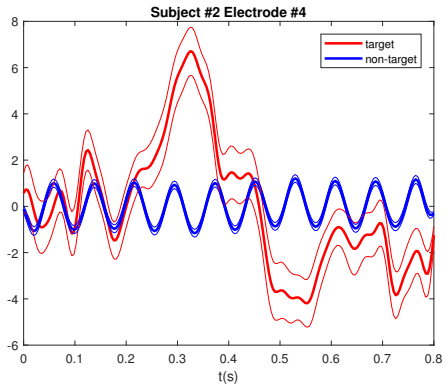
part3

we chose subject number 2.






Subject #2 Electrode #3
target
non-target
t(s)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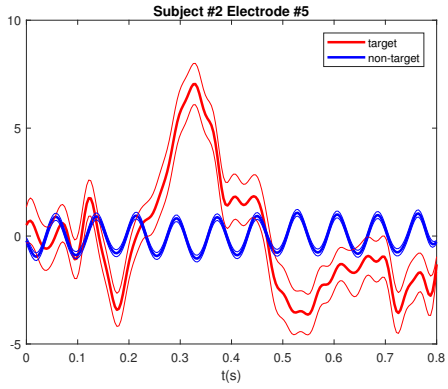
non-target
t(s)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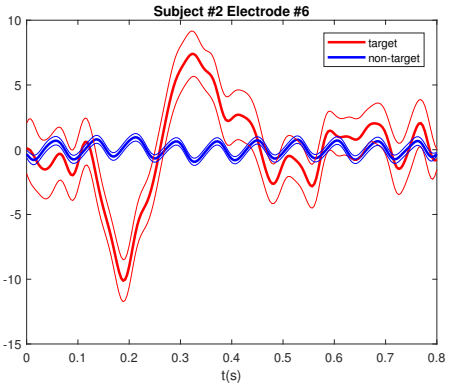
non-target
t(s)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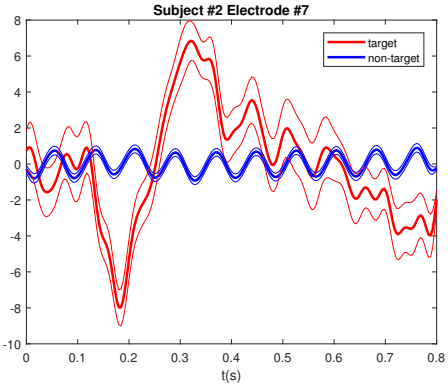
target
non-target
t(s)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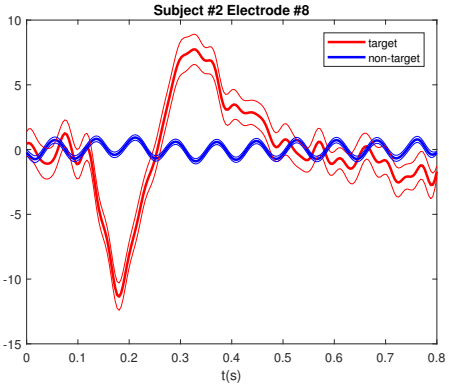
target
non-target
t(s)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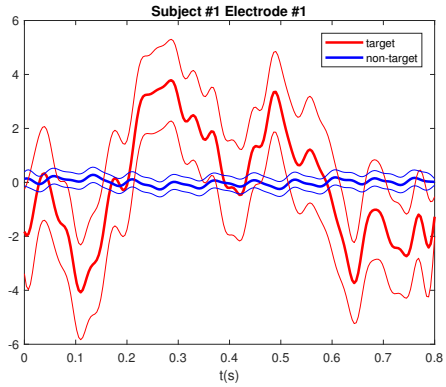
target
non-target
t(s)

S1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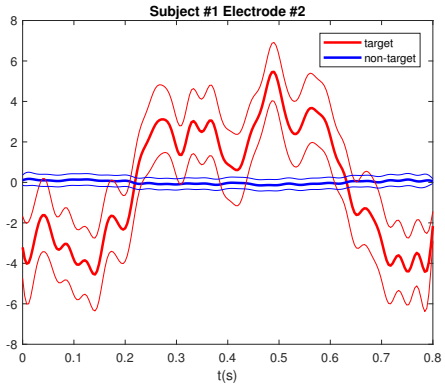
target
non-target
t(s)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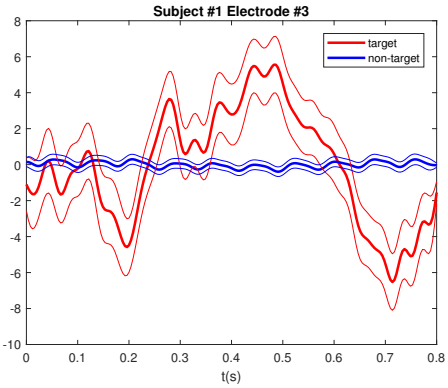
target
non-target
t(s)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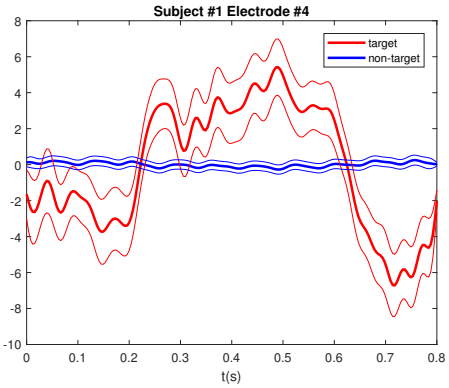
target
non-target
t(s)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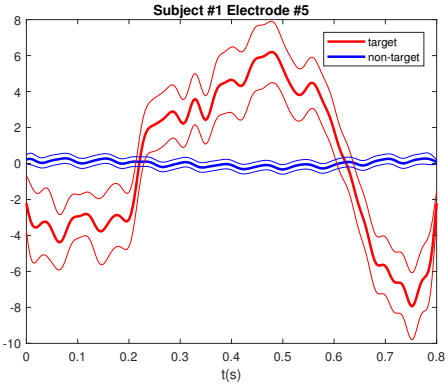
target
non-target
t(s)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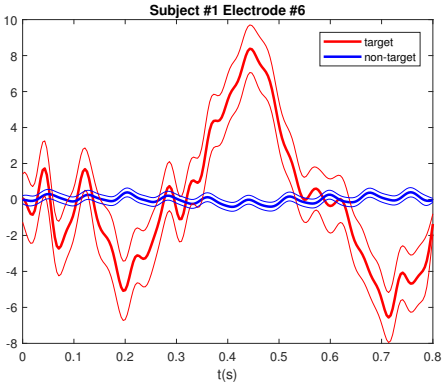
target
non-target
t(s)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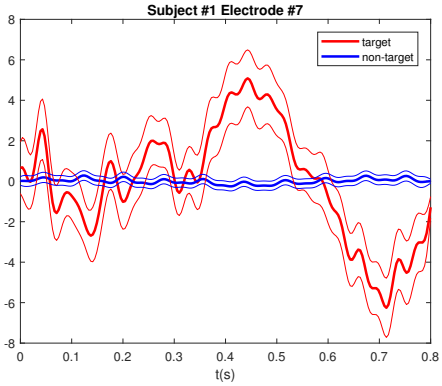
target
non-target
t(s)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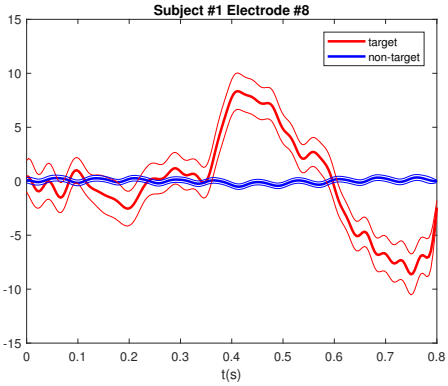
target
non-target
t(s)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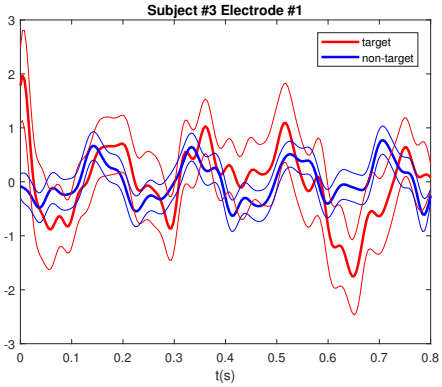
target
non-target
t(s)

S3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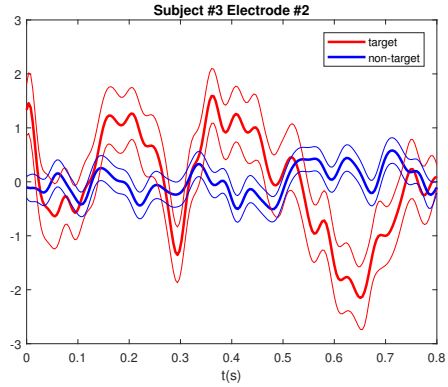
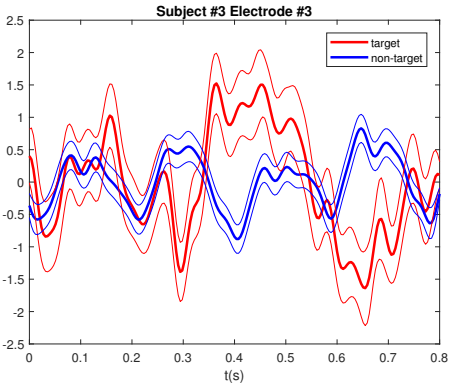
target
non-target
t(s)


Subject #3 Electrode #2
target
non-target
t(s)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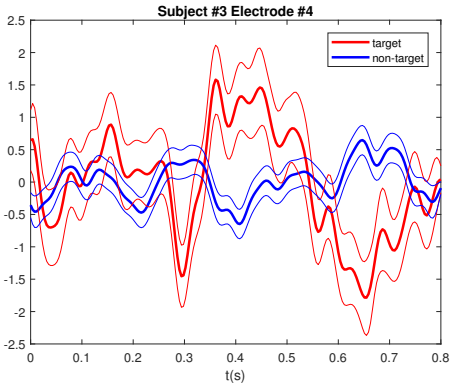
target
non-target
t(s)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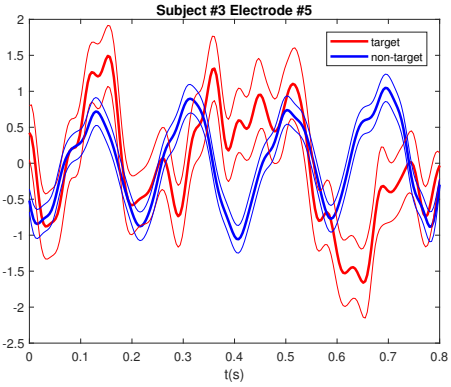
target
non-target
t(s)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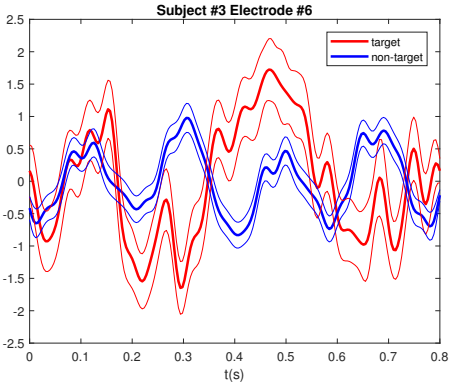
target
non-target
t(s)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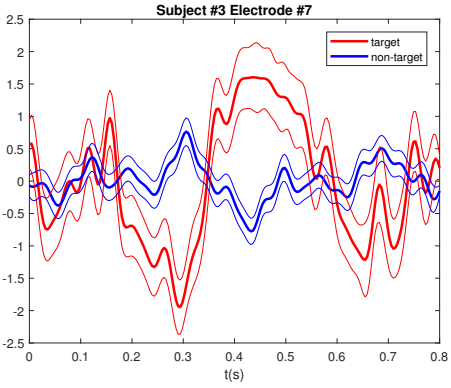
target
non-target
t(s)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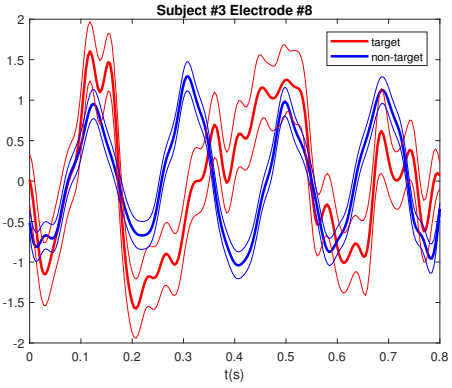
target
non-target
t(s)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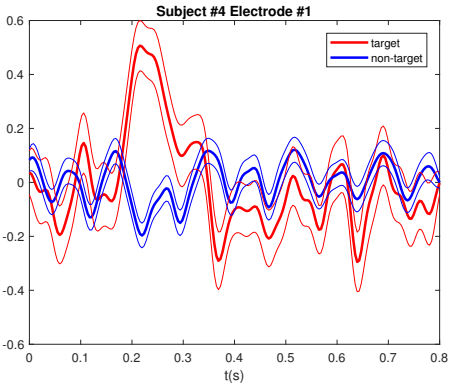
target
non-target
t(s)

S4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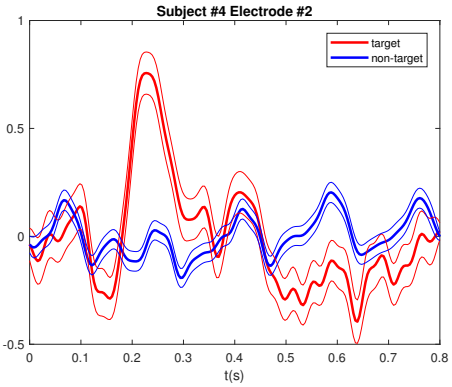
target
non-target
t(s)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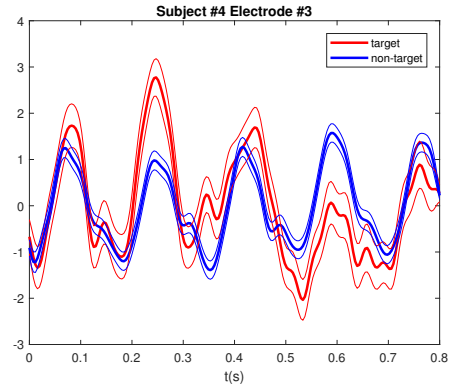
target
non-target
t(s)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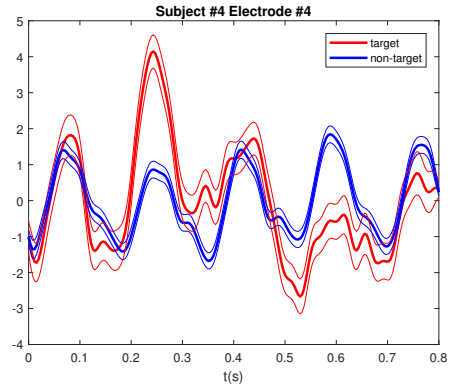
target
non-target
t(s)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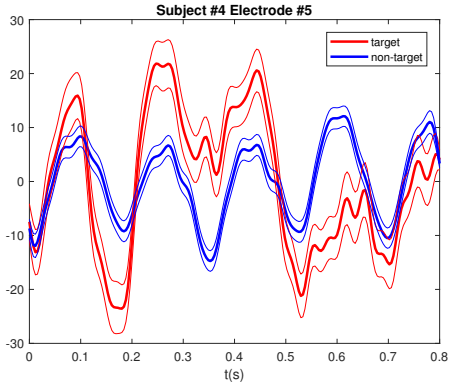
target
non-target
t(s)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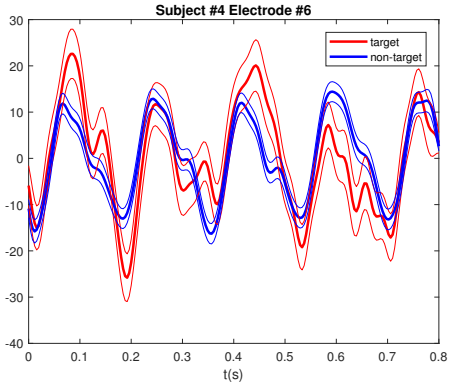
target
non-target
t(s)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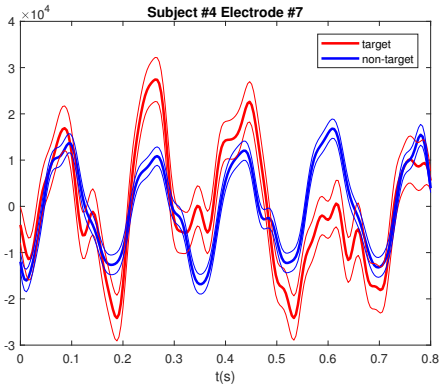
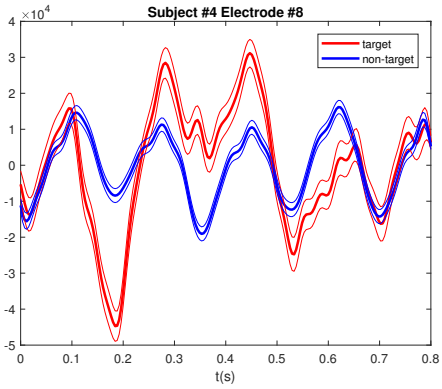
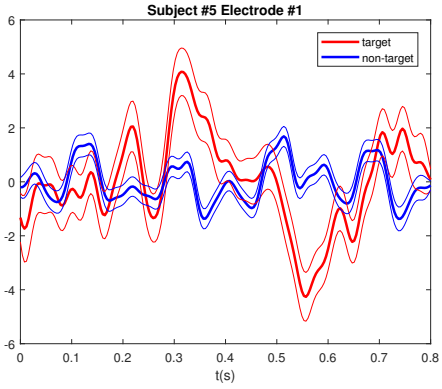
target
non-target
t(s)


Subject #4 Electrode #7
×10^4
target
non-target
t(s)


Subject #4 Electrode #8
×10^4
target
non-target
t(s)

S5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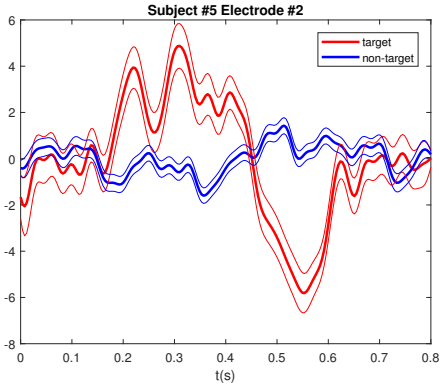
target
non-target
t(s)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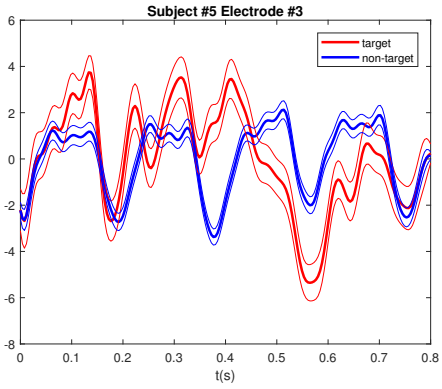
non-target
t(s)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non-target
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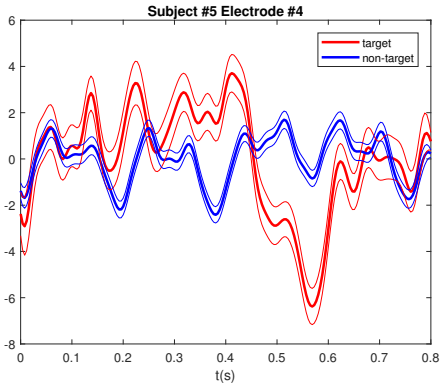
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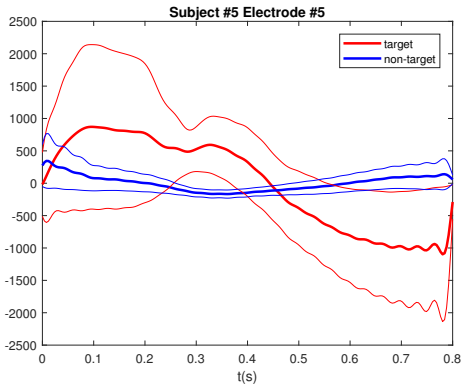
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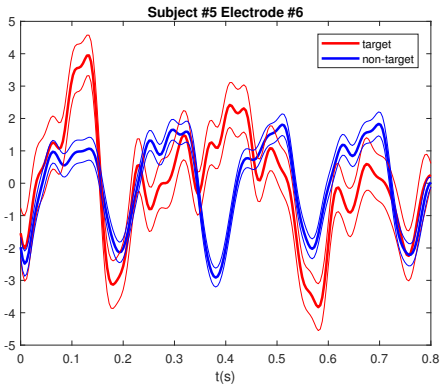
target
non-target
2500
2000
1500
1000
500
0
-500
-1000
-1500
-2000
-2500
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
t(s)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target
non-target
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-1
-2
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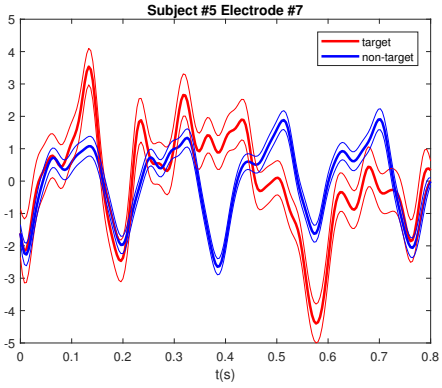
0.3
0.4
0.5
0.6
0.7
0.8
t(s)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target
non-target
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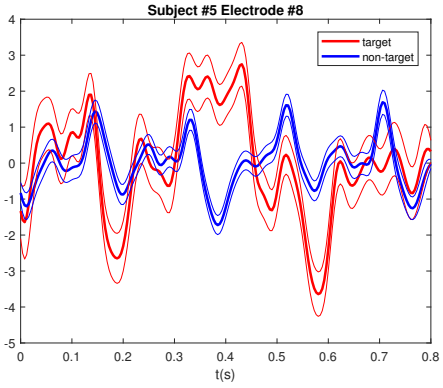
0.5
0.6
0.7
0.8
t(s)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target
non-target
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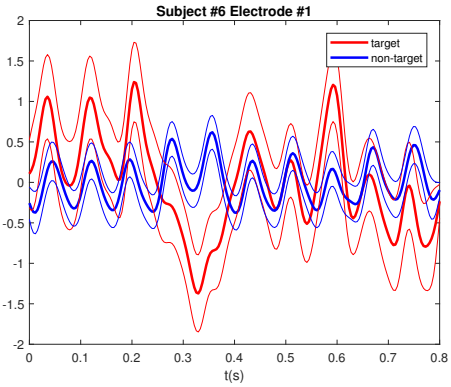
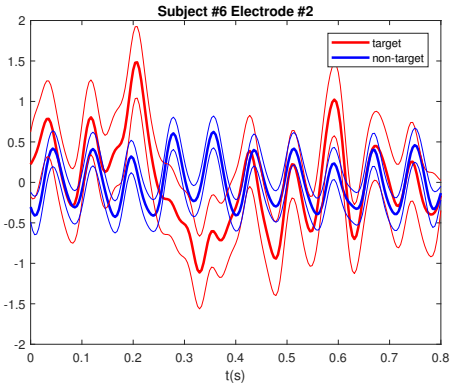
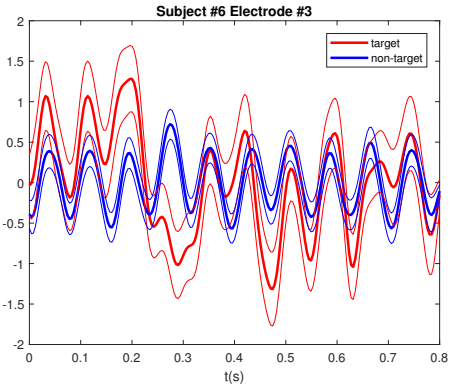
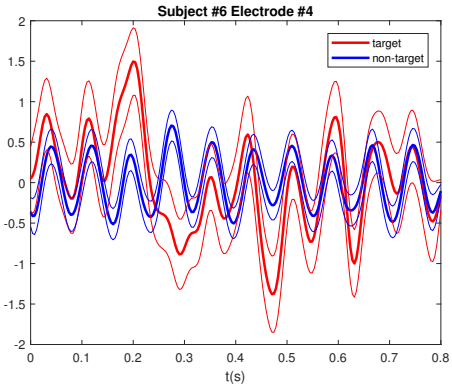
0.3
0.4
0.5
0.6
0.7
0.8
t(s)

S6


Subject #6 Electrode #1
target
non-target
t(s)


Subject #6 Electrode #2
target
non-target
t(s)


Subject #6 Electrode #3
target
non-target
t(s)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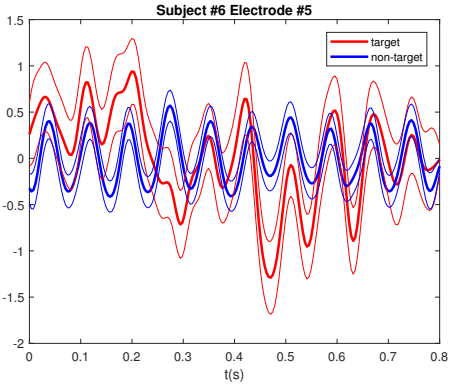
target
non-target
t(s)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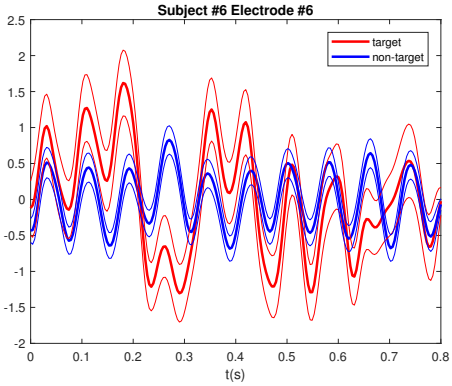
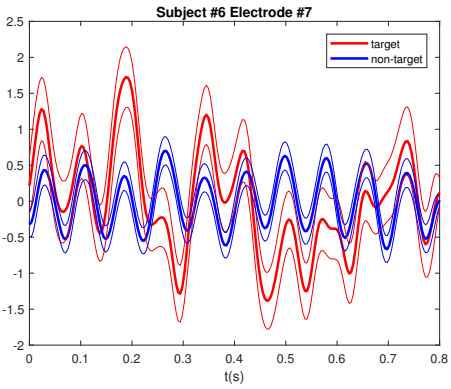
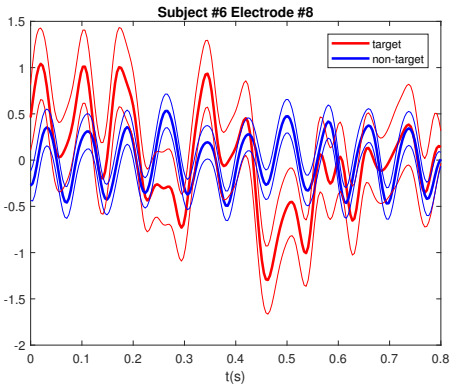
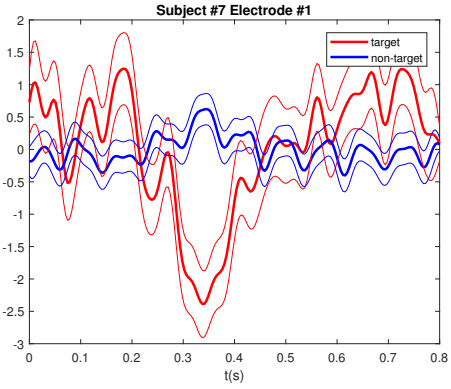
target
non-target
t(s)

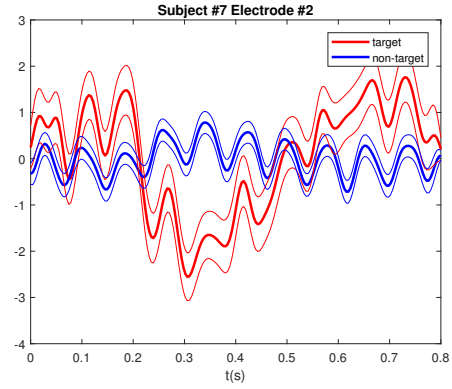

Subject #6 Electrode #6
target
non-target
t(s)


Subject #6 Electrode #7
target
non-target
t(s)


Subject #6 Electrode #8
target
non-target
t(s)

S7


Subject #7 Electrode #1
target
non-target
t(s)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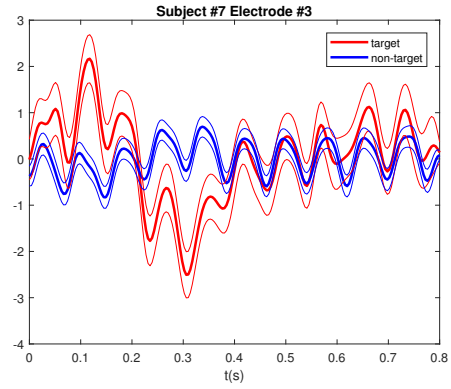
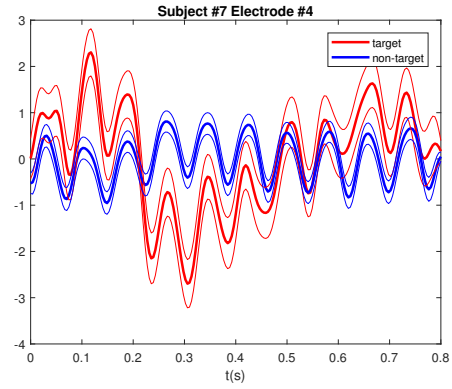
target
non-target
t(s)


Subject #7 Electrode #3
target
non-target
t(s)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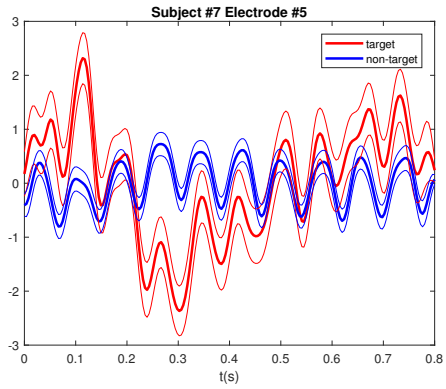
target
non-target
t(s)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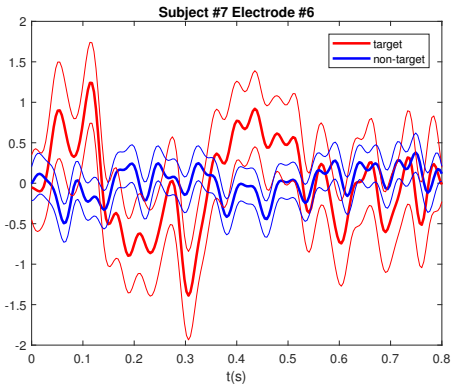
target
non-target
t(s)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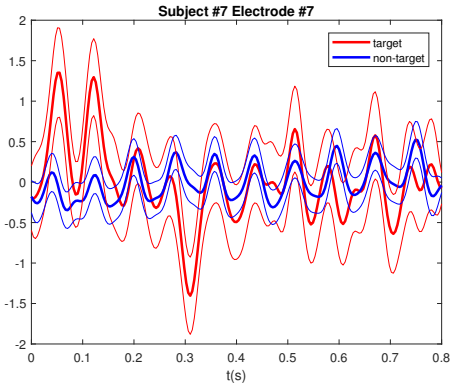
target
non-target
t(s)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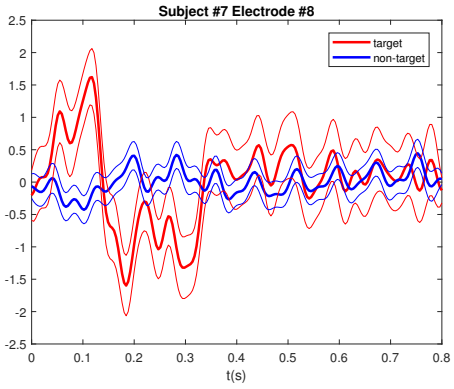
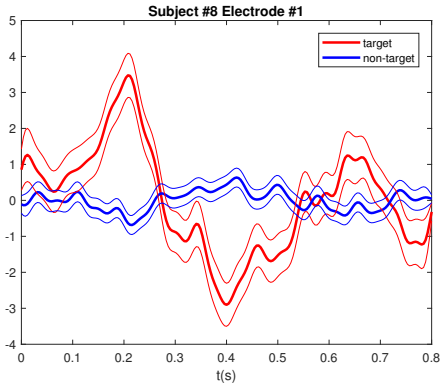
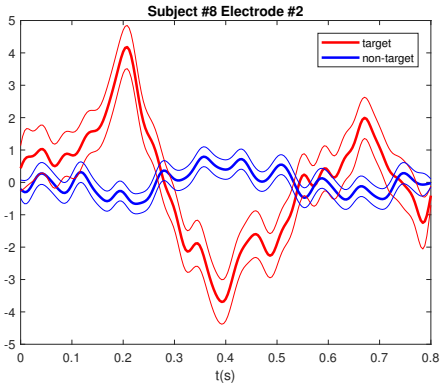
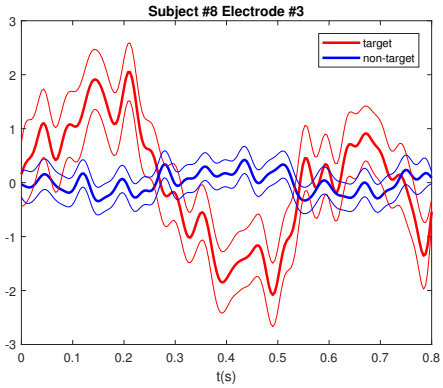
target
non-target
t(s)


Subject #7 Electrode #8
target
non-target
t(s)

S8


Subject #8 Electrode #1
target
non-target
t(s)


Subject #8 Electrode #2
target
non-target
t(s)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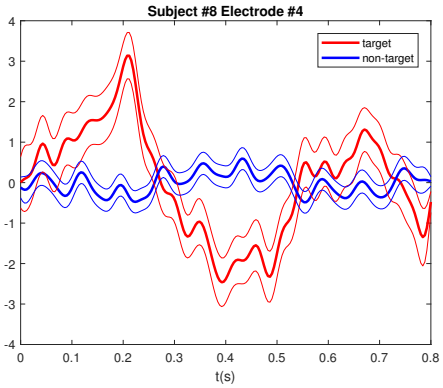
target
non-target
t(s)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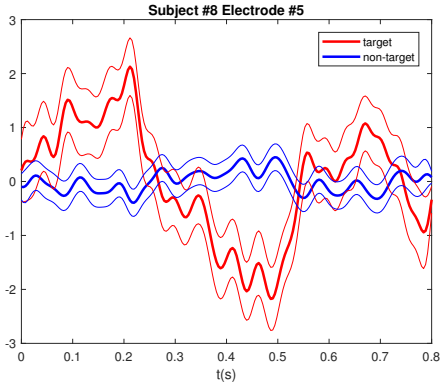
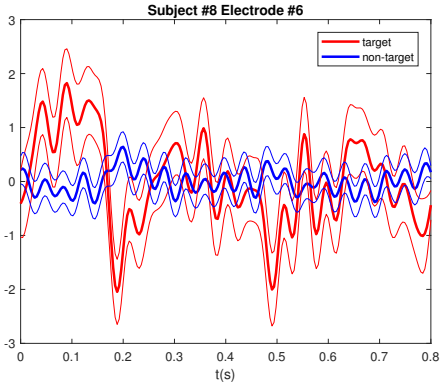
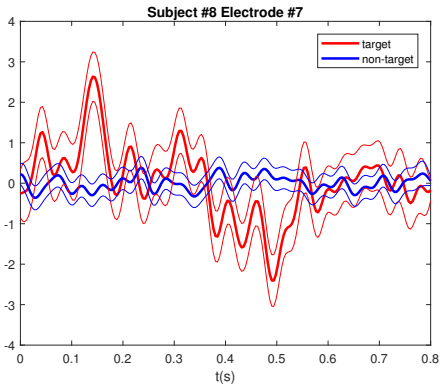
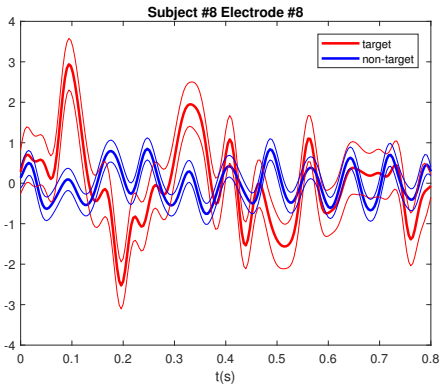
target
non-target
t(s)

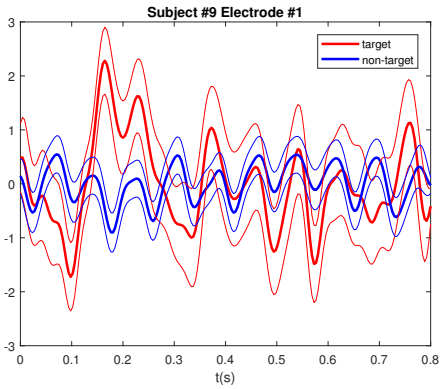

Subject #8 Electrode #5
target
non-target
t(s)

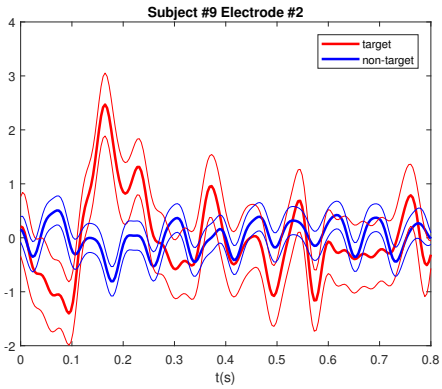

Subject #8 Electrode #6
target
non-target
t(s)

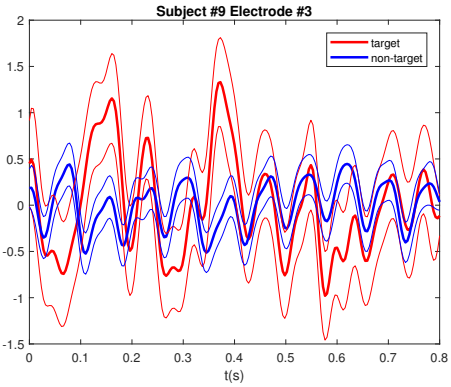

Subject #8 Electrode #7
target
non-target
t(s)

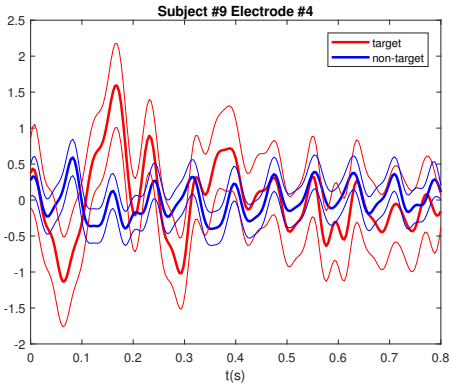

Subject #8 Electrode #8
target
non-target
t(s)

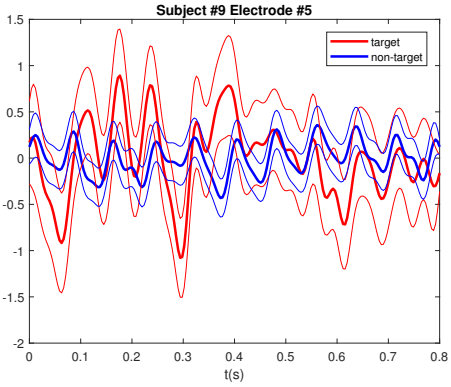
S9

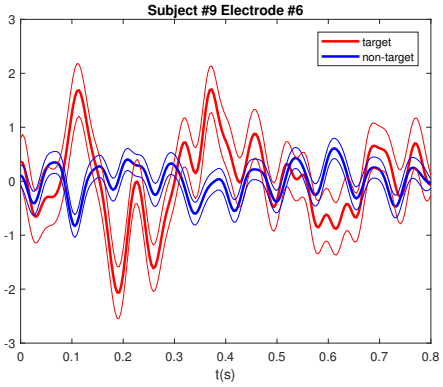

Subject #9 Electrode #1
target
non-target
t(s)

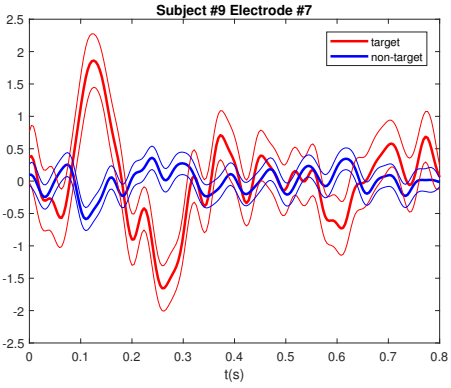

Subject #9 Electrode #2
target
non-target
t(s)

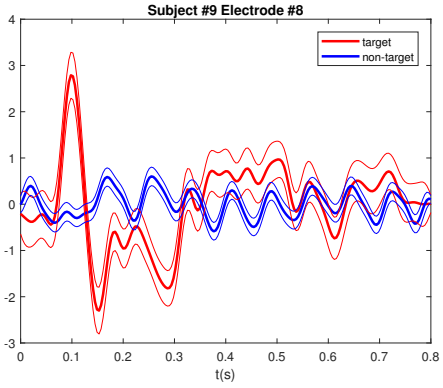

Subject #9 Electrode #3
target
non-target
t(s)


Subject #9 Electrode #4
target
non-target
t(s)

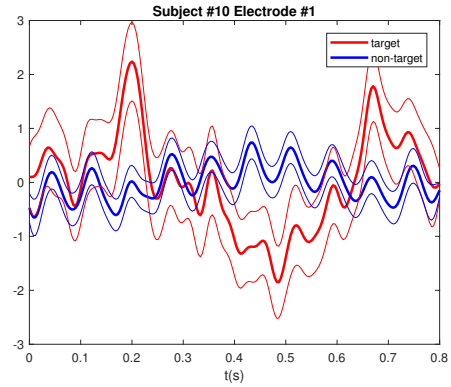

Subject #9 Electrode #5
target
non-target
t(s)

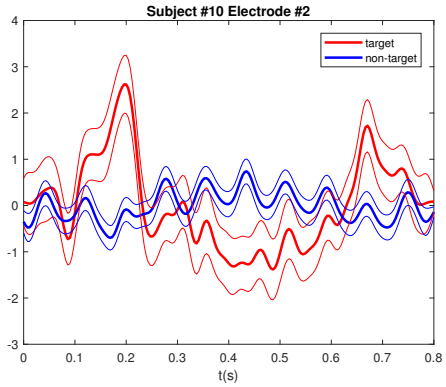

Subject #9 Electrode #6
target
non-target
t(s)

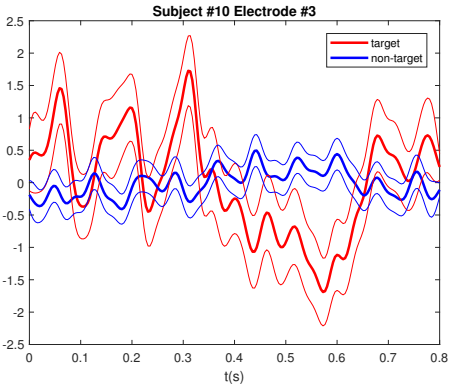

Subject #9 Electrode #7
target
non-target
t(s)

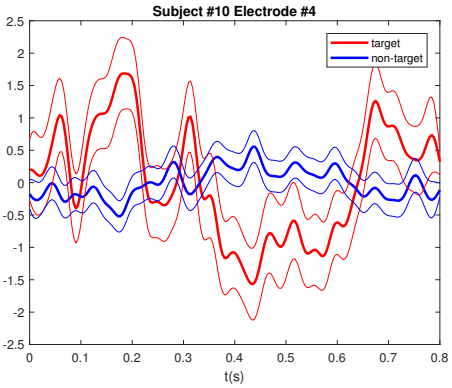

Subject #9 Electrode #8
target
non-target
t(s)

S10


Subject #10 Electrode #1
target
non-target
t(s)


Subject #10 Electrode #2
target
non-target
t(s)


Subject #10 Electrode #3
target
non-target
t(s)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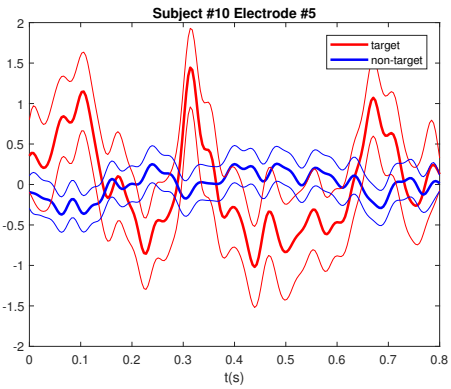
target
non-target
t(s)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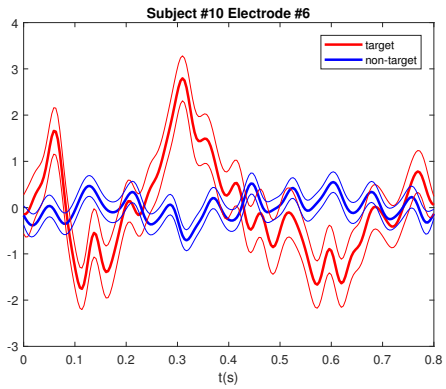
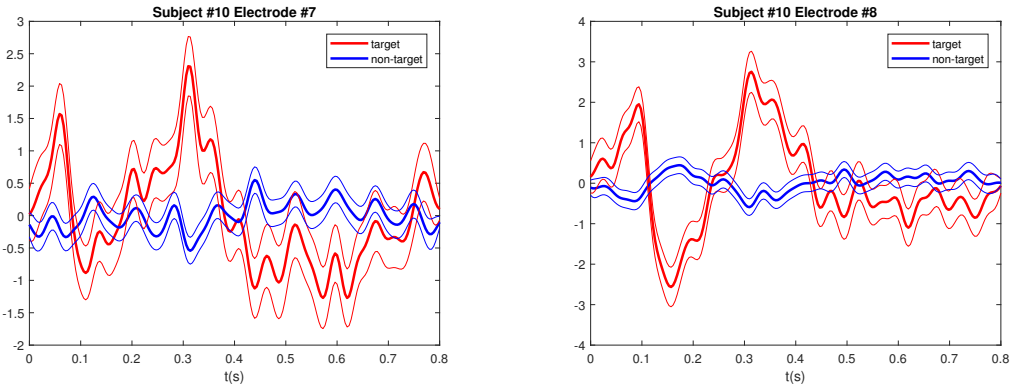
target
non-target
t(s)


Subject #10 Electrode #6
target
non-target
t(s)



question 3

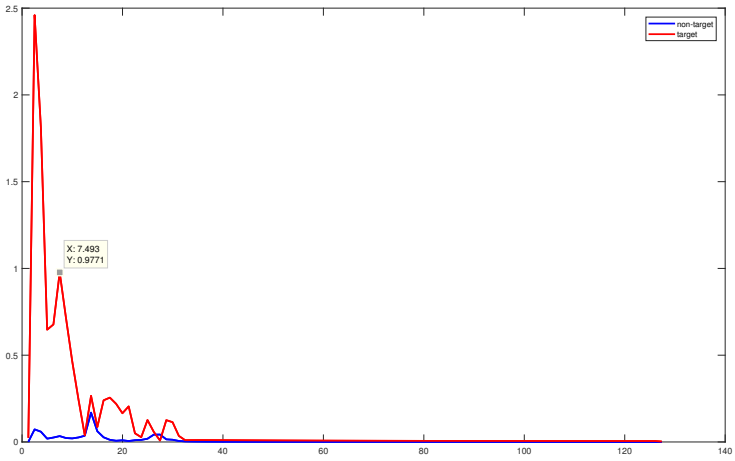


Figure 1: comparing frequency content of each target or non-target

when there is no deviant stimuli our brain works in normal way and it assumes that close future is same as present time and as we know from Neuroscience course, when we stair at some palace without attention the most part of frequency content is belong to alpha wave and we don't have much beta wave, but as soon as deviant stimulus is shown to us, we got anxious and beta wave appears. also delta will appear because of continue attention task. when there is no deviant stimulus, the duty of processing is on upper layers of brain, but if stimulus is deviant then lower layer process.

upper layers predict close future and they emit oscillating wave.

question 4

if we want to say that which electrode is better for identifying target from non-target stimuli we have to searching for an electrode that has maximum difference between target and non-target ERPs and also higher p300 amplitude. this criteria is not too accurate but we couldn't have found a mathematic criteria for that. maybe we can say if target and non-target ERPs have lower correlation, then correspond electrode is better for identifying. or also we can take a look at frequency content of both in each electrode. but here we just determine the best electrode and the best time domain by eyes.

subject number	best electrode	P300 time
sub1	8	400-600 ms
sub2	7	200-400 ms
sub3	7	400-600 ms
sub4	2	200-400 ms
sub5	2	400-600 ms
sub6	1	400-600 ms
sub7	6	0-200 ms
sub8	5	0-200 ms
sub9	7	0-200 ms
sub10	6	200-400 ms

question 5

a

in all subjects and almost all electrode we can observe this phenomenon. as it is obvious from all pictures attached in question 2.

b

p300 time and best electrode are different between subjects so the answer is no.

c

for first and second subjects we have SC paradigm and for the left we have RC. in SC paradigm amplitude of non-target ERP is much less than target.

and also amplitude of target ERP in SC is less than RC. and this is what paper claimed.

d

we believe that speller will have a high accuracy response from S1 and S2 and S5 and S8 and S9 and S10. because there is a big difference between target ERP and non-target ERP but in other subjects there is no big difference in ERPs.

question 6

we conclude that if there is more differences between two ERPs, our speller will act better. so we expect that, despite of, in SC we have less target stimuli but there is much more differences in ERPs so we will get good answer from SC paradigm.

part4

question 2

subject number	test-target	test-total	train-target	train-total
sub1	2.6%	96.2%	61.3%	98.3%
sub2	25.3%	97.2%	76%	99.1%
sub3	48%	73.6%	76%	93.1%
sub4	48%	78.4%	85.3%	95.5%
sub5	54.6%	77%	89.3%	94.6%
sub6	38.6%	73%	74.6%	90.6%
sub7	44%	77.55%	85.33%	94.7%
sub8	64%	83.88%	88%	95.2%
sub9	64%	84%	82.6%	94.7%
sub10	53.3%	82.5%	89.3%	94.4%

subject number	train-target-CV	train-total-CV
sub1	8%	95.9%
sub2	30.6%	97.7%
sub3	37.3%	72.4%
sub4	53.3%	78.5%
sub5	56%	78.8%
sub6	28%	69.2%
sub7	46.6%	76.1%
sub8	48%	78%
sub9	53.3%	80.1%
sub10	57.3%	78.8%

we analyzed this 3 number and conclude that all cross-validated train data accuracy percentage is less than without cross-validation train data and that is because of in cross validation we shuffling and dividing data in k groups with equal number of elements and in we train the classifier with k-1 groups and validate it with 1 group for k time. so the accuracy is much trustworthy. but if we train the classifier with some matrix and validate it with the same matrix the high accuracy is predictable. cross-validated train data accuracy percentage is close to test accuracy just because of cross-validation.

question 3

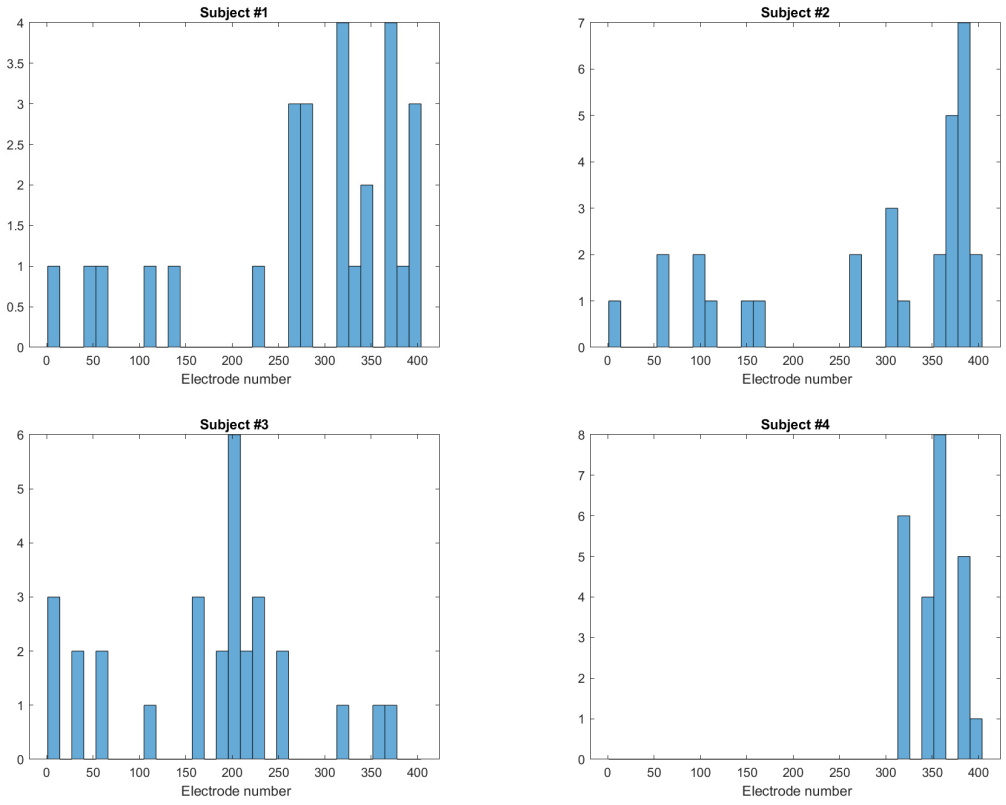
we have same algorithm for RC and SC paradigm.

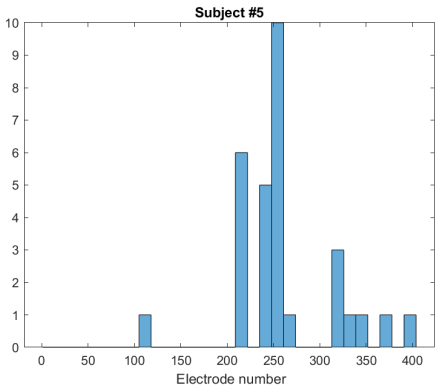
algorithm

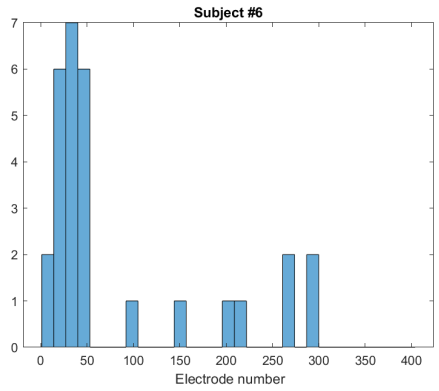
we have a prediction vector for test data.first we organize it in order of time. then we break this vector in 180-element groups and then we break each group to the 15 twelve-element groups. each 180 group is for one character. for each character we have 15 trials. in each trial it is likely to have some targets which are distinguished by classifier. we determine target character in each trial and finally take mode from them and introduce it as target character.

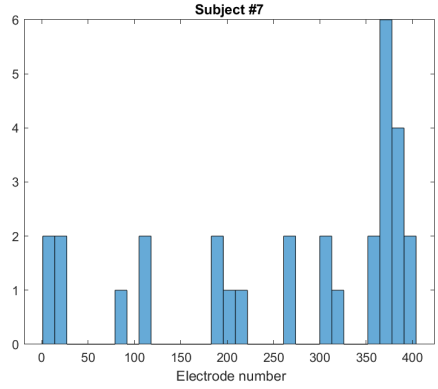
subject number	WORD	percentage
sub1	A0KKK	20%
sub2	LUKAS	100%
sub3	LUGAP	60%
sub4	FUJAA	40%
sub5	EATER	80%
sub6	WU2YD	20%
sub7	XAHER	60%
sub8	WATEL	80%
sub9	WATEP	80%
sub10	WASER	80%

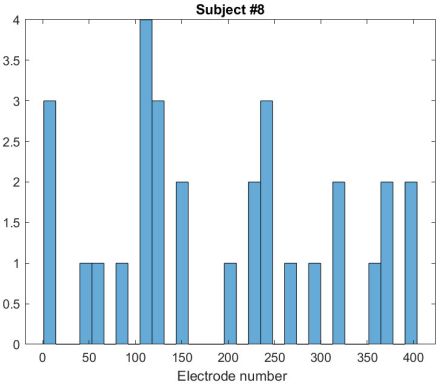
question 4



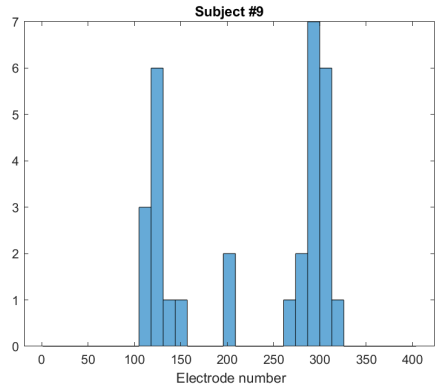

Subject #5
Electrode number

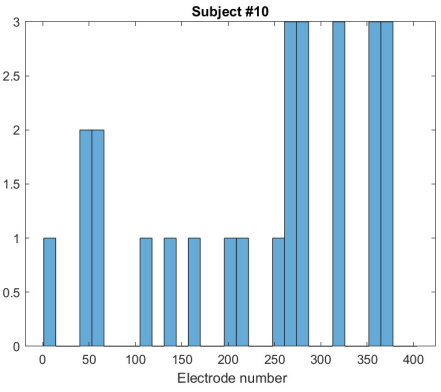

Subject #6
Electrode number


Subject #7
Electrode number


Subject #8
Electrode number

S9


Subject #9
Electrode number


Subject #10
Electrode number

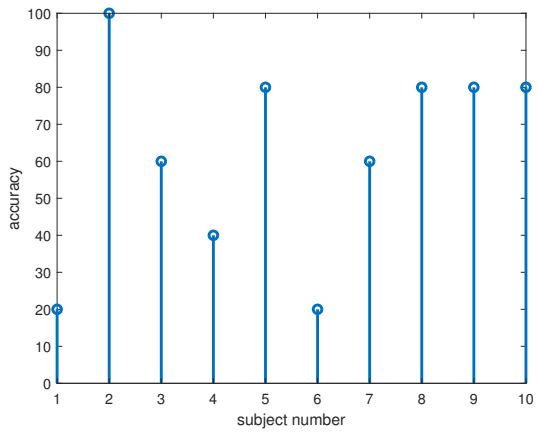
we drive first 30 important features of each subject. and 4 bins make a electrode. a electrode with larger number is the most important electrode and also 0-200 ms and 200-400 ms and 400-600 ms and 600-800 ms are correspond to first to forth bin of each electrode.

subject number	best electrode	important time
sub1	8	0-200 ms
sub2	8	400-600 ms
sub3	5	600-800 ms
sub4	7	600-800 ms
sub5	5	600-800 ms
sub6	1	400-600 ms
sub7	8	0-200 ms
sub8	3	0-200 ms
sub9	7	600-800 ms
sub10	6	200-400 ms

for some electrodes and also some time domain our decision is adapted to our method.

question 5

a



b

just for one subject.

c

no,as we know brain response is individual for each person and we can't compare different brains to each other.

d

the average of RC paradigm is much higher then SC,but we choose SC paradigm just because we believe that it is more easy to reach high accuracy in SC than RC, because we got 100 % for on subject in SC but we couldn't get 100 % accuracy for RC .

e

if we don't consider subject number one our result is Compatible to 4-5-d

question 6

in SC paradigm the number of target stimuli is much less than RC. in the other hand difference between target ERP and non-target ERP in SC is much higher than RC. and also many other differences, but this and many other papers claim that SC paradigm is better than RC and our result of subject 2 prove our claim.

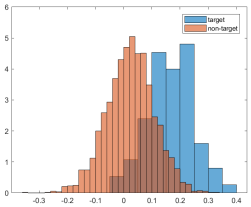
باسمه تعالی

قسمت پنجم

در این قسمت قصد داری تا چند معیار را برای جداسازی تارگت ها و غیرتارگت ها ارایه بدهیم.

روش اول مبتنی بر Regression

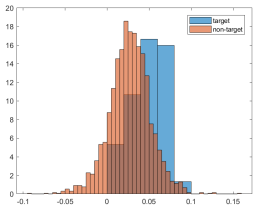
در ابتدا داده های مرتبط با سابجکت شماره ۲ را بدست بازیابی می کنیم و تمام عملیات را روی این سابجکت انجام می دهیم. در ابتدا می دانیم که رگرسیون روشی است که به وسیله ی آن می توانیم از تعدادی نقطه در یک فضای n بعدی خط بگذرانیم. حال به وسیله ی آن می توانیم به بردار ویژگی های خود یک ستون اضافه کنیم که برای بردار های تارگت عدد متناظر ۱ باشد و برای غیرتارگت ها عدد متناظر ۰ باشد. کاری که می کنیم این است که حال ماتریس تست خود را به عنوان ورودی تابع predict می دهیم و ستون آخر را بدست می آوریم و دقت را می سنجیم. مشاهده می کنیم ۲ توزیع تا حد خوبی از هم



جدا شده اند. و مقدار p-value برای ستون آخر انقدر بزرگ نیست که غیر قابل اعتماد باشد.

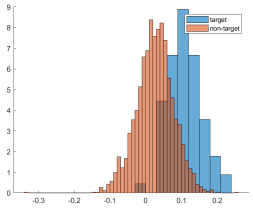
روش دوم مبتنی بر ICA

در این روش ابتدا تلاش می کنیم که فضای P-300 را بسازیم. می دانیم که وظیفه ی ICA یافتن بردار های منبع هست، برای مثال اگر ما تعدادی نقطه در یک فضای n داشته باشیم آنگاه با این الگوریتم می توانیم به همان تعداد بردار پیدا کنیم که با ضرایبی هر کدام از نقاط را می سازند. اگر ما تمام بردار های متاظر با تارگت و غیرتارگت را در بردار های منبع ضرب کنیم، می توانیم یک ماتریس ویژگی جدید داشته باشیم که به وسیله ی آن می توان بار دیگر با روش مطرح شده در قسمت اول، صحت را روی داده های تست بدست آورد. مشاهده می کنیم که همان عمکرد قسمت اول بهتر بود.



روش سوم مبتنی بر PCA

در این روش بر روی بردار ویژگی ترین PCA را اعمال می کنیم و بردار هایی را نگه می داریم که تا ۹۰ درصد اطلاعات را داشته باشند در اینجا می شود ۶۹ بردار. سپس همانطور که در قسمت اول انجام دادیم، هیستوگرام جدا سازی را رسم می کنیم.
مشاهده می شود که این روش نیز روش قابل قبولی برای جداسازی هست.



روش چهارم مبتنی بر α و β

با توجه به انرژی در باند آلفا و بتا و تتا با توجه به ویژگی های تمرکزی شاید بتوان از انرژی در این ۳ باند فرکانسی برای دسته بندی استفاده کرد. اصلا خوب عمل نمی کند.