Advance Neuroscience HW2

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Step 1 - Analysing the Average PSTH of the Units

First, we plot the PSTH of all condition for some random units in figure 1. The PSTH is filtered by a moving average filter with window of length 9. From the figure we can see there is a correlation between the conditions of a unit. Although, There are differences between units. The units differ in firing rates and shape. But almost all of them show a sign of change at around $1.5ms$ after the stimulus onset (which is denoted by the red dotted line). Also we may be able to classify units by their response shapes. e.g. units 1, 25, 49, 97 and 169 have same shapes specially 25, 49 and 169. Units 73, 121 and 145 are also about the same.

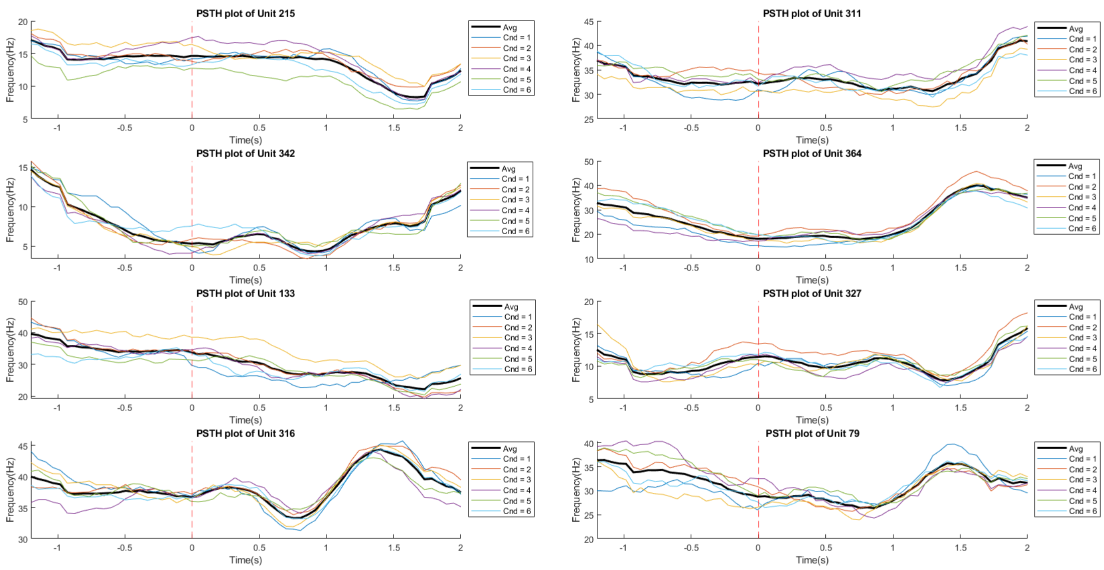

Figure 1: PSTH plot all conditions for some random units. The bold black line is the average between conditions and the stimuli onset is denoted by the dotted red line

So as we see a similarity between conditions of a unit, we may take the average of the conditions as a reference to compare the units with each other. Figure 2 shows such plot. As apparent in the figure, we have two time points that we can obviously see a similar behavior between the units. The mentioned time points are denoted in the plot by red dotted lines. It may show that although the units may have different frequency biases and different reactions to stimuli, but they also show some synchronized changes. For example right after the $t = -1$ and $t = 1.7$ we can see a sudden change of frequency in most of the units and it look like two broken lines in plot. So the conclusion is that the units may have similar behavior that we must pay attention to.

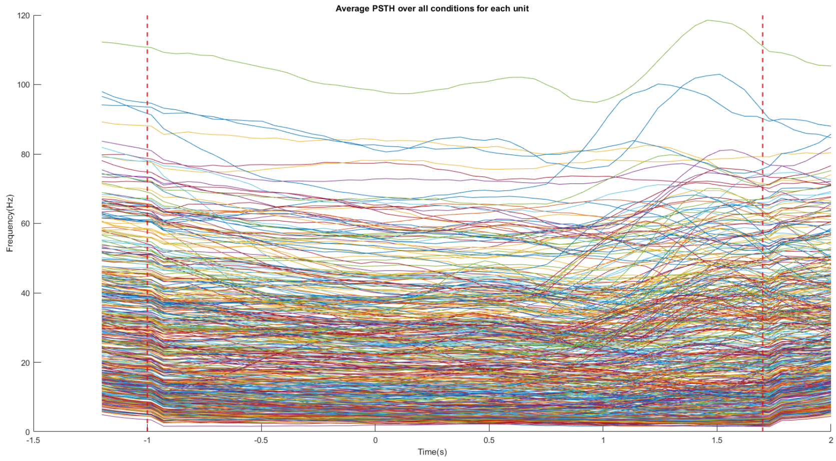

Figure 2: PSTH averaged over over all conditions for each unit. two dotted red lines are at -1 and 1.7 respectively

At the same time as making the plot in figure 2, The maximum minus the minimum frequency of each unit has been saved to find the most variable unit with respect to frequency. A total of 10 units are chosen for the next part of the analysis. We want to check whether the rewards and cue locations have an effect on the average PSTH of these units.

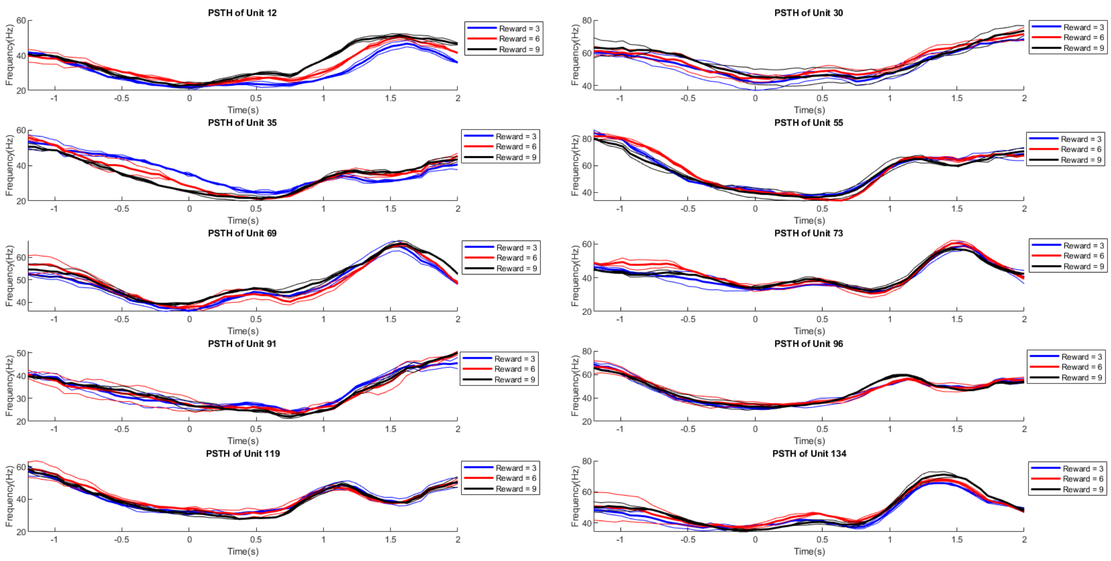

Figure 3: Average of PSTH of the conditions with same reward

For the chosen units, average of PSTH over same rewards is calculated and results can be seen in figure 3. The red, blue and black bold lines are average of conditions with reward of 3, 6 and 9 respectively. In some of the plots after the stimuli onset a tendency of rising in black line can be seen. Also in almost 60% of the units, the black line end up above the other two lines which may suggest more acitivy of neurons for more rewards. But yet the difference is not that big of a deal so we can not conclude anything yet. Furthermore, same plots was made for 10 random units for a couple of times and the difference was even less. Though it could be due to the fact that not all neurons encode the reward.

Similar evaluations was done for cue locations and no eye catching difference was seen in the PSTH of the units. (figure 4)

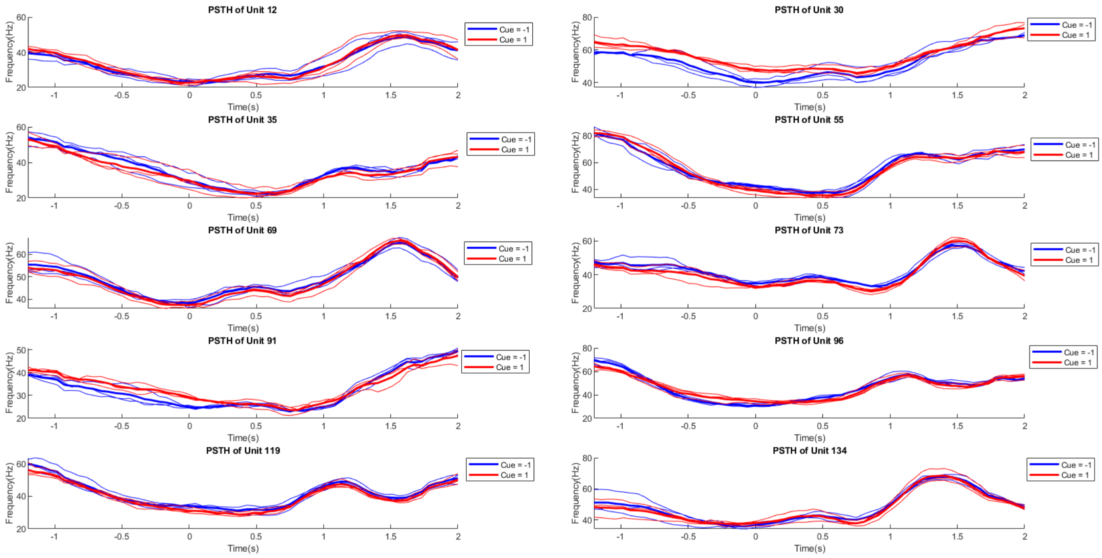

Figure 4: Average of PSTH of the conditions with same cue locations

Here we have brought some similar responses in figure 5 and 6.

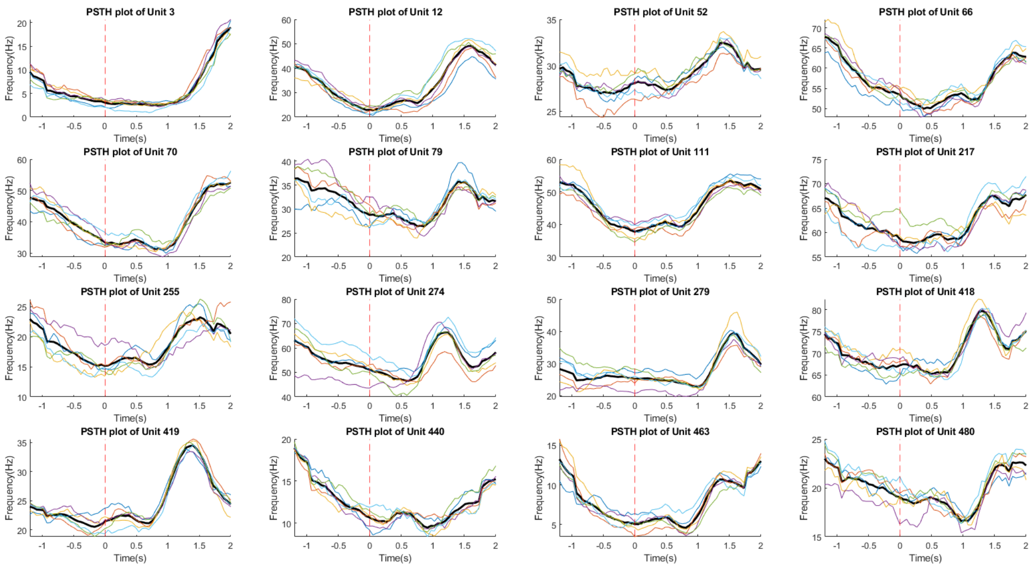

Figure 5: Similar response category 1

In figure 5, the frequency after the stimuli onset drops a little and then rises. In most of the cases it has a peak at around $1.5ms$ and then drops But in some of them it continues to rise.

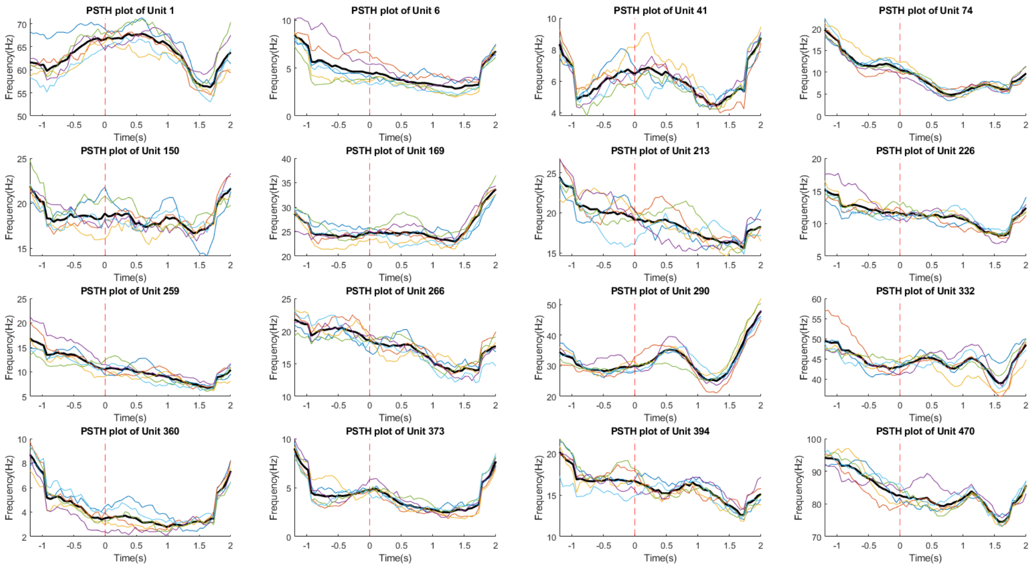

Figure 6: Similar response category 2

In figure 6, we mostly see a drop of frequency after the stimuli onset. The frequency drops until around $1.5ms$ and again rises after some time.

As a conclision we can point that the stimuli causes a rise in frequency eventually in almost all the units. But units' behaviors defer right after the stimuli onset. Some rise and some drop. Also $t = 1.5ms$ is common time between most of the units which either there is a peak or a minimum.

To understand if there is a discrimination of behavior between units around $t = 1.5ms$, we normalize each unit PSTH to its maximum and calculate the ditributions of average frequency in $1.4 < t < 1.6$. The distributions are calculated for all conditions, rewards and cue locations. Figure 7 shows the mentioned plot for all conditions. As it is apparent from the plots, for all conditions we almost have the same distributions. The red lines show the distribution mean and the width of the two black lines shows the value of std. Also as different units have different frequency biases, the PSTH of each unit is normalized to its maximum so we are able to put frequencies together.

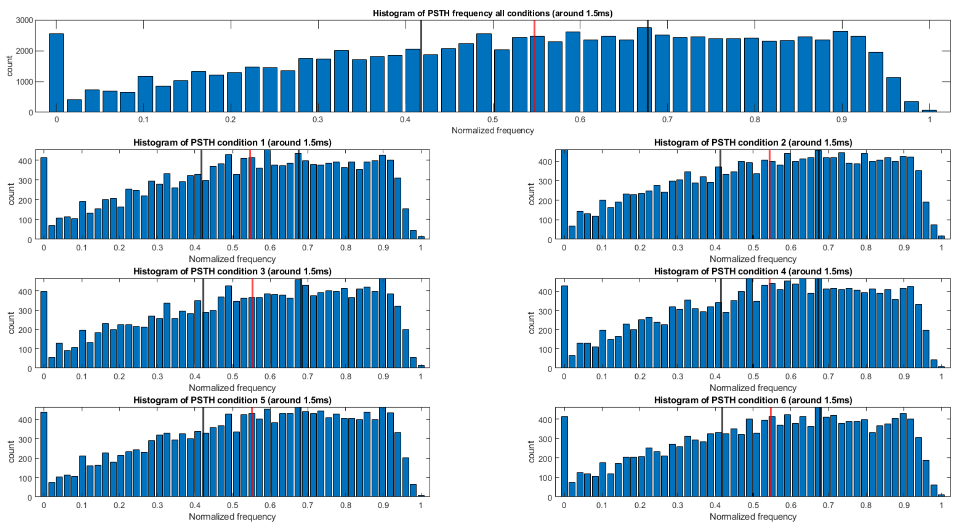

Figure 7: PSTH distribution for all conditions at $t = 1.5ms$

By looking at the figure 7 we suggest that the distribution does not depend on the conditions. To check the same thing for different rewards and cue locations, we have figure 8. As apparent from the figure the same thing happens here so the rewards and cue locations also do not change the distribution of firing rate.

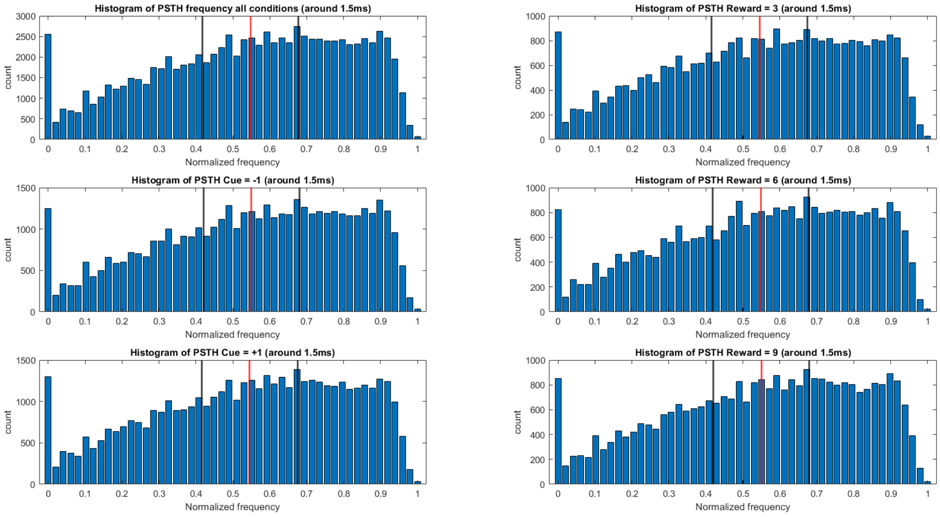

Figure 8: PSTH distribution for all parameters at $t = 1.5ms$

Now we check how the time changes the firing rate distribution. (Figure 9) From the figure we can see that after the stimuli onset frequency drops (as we saw before in the PSTH plots) and then it continues to rise and recovers its resting distribution at around $t = 2ms$. (note that the distribution of $t = -1.2ms$ is much like the distribution in $t = 2ms$ and thats why we used the word 'recover')

Also the mean firing rate changes obviously at different times and it is apparent from the figure but the variance does not change and it may explain why we have different response shapes between units. But the distributions show that although there are differences between single units, but we may get a good idea of how the system works we look at the population activity distribution. Another thing to notice in figure 9 is that a large amount of units become muted between stimuli onset and $t = 1.5ms$ which is apparent from the first bar of the three middle plots.

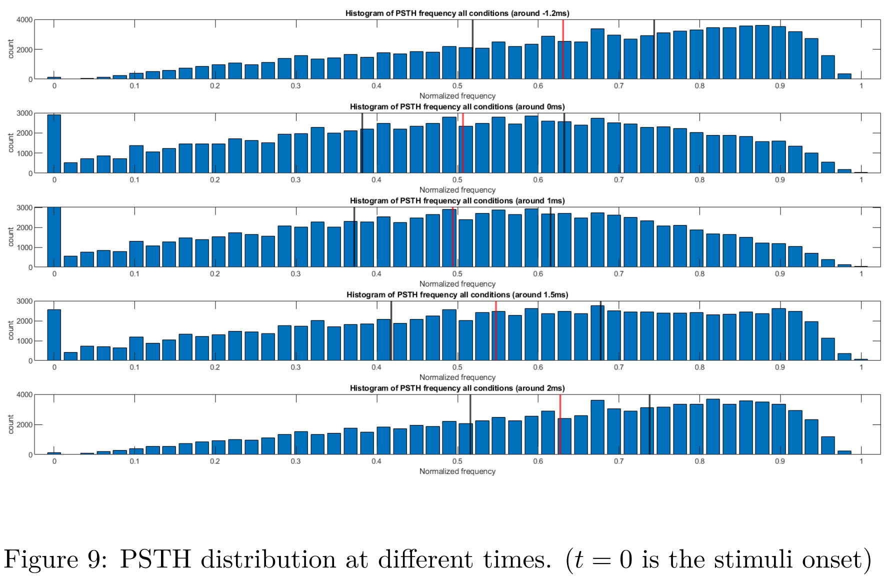

Figure 9: PSTH distribution at different times. ($t = 0$ is the stimuli onset)

Step 2 - GLM Analysis of Single Units

Using 'fitglm()' function in MATLAB, linear models are fitted to each unit and the p-value of the coeficients are calculated by 'coefTest()' function. Then the units with a p-value of less than 0.05 are saved in a vector. The units are as in table 1.

Table 1: Units and p-values

12	13	15	17	50	52	53	72	109	163	165	172
0.000382	0.0451	0.0023	0.0186	0.0232	0.0447	0.0394	0.0401	0.033	0.0106	0.0323	0.0135

176	243	272	291	297	347	390	403	411	437	478
0.0324	0.0316	0.0405	0.0013	0.0022	0.0427	0.0357	0.016	0.0171	0.0054	0.0139

Now in order to investigate the connection between stimuli and single units, we plot the firing rates of the most significant units in respect to each other. But as the dimension is 23 and we can not visualize more than 3 dimensions, we just show the results for 2 dimentions. (2 of the units are selected randomly and the plots are made) Figure 10 is the firing rates of units 12 and 390 with respect to each other at 6 different time. The red and black ellipses are centered at the mean of each condition and the long and short diameters show the std of each unit in the condition.

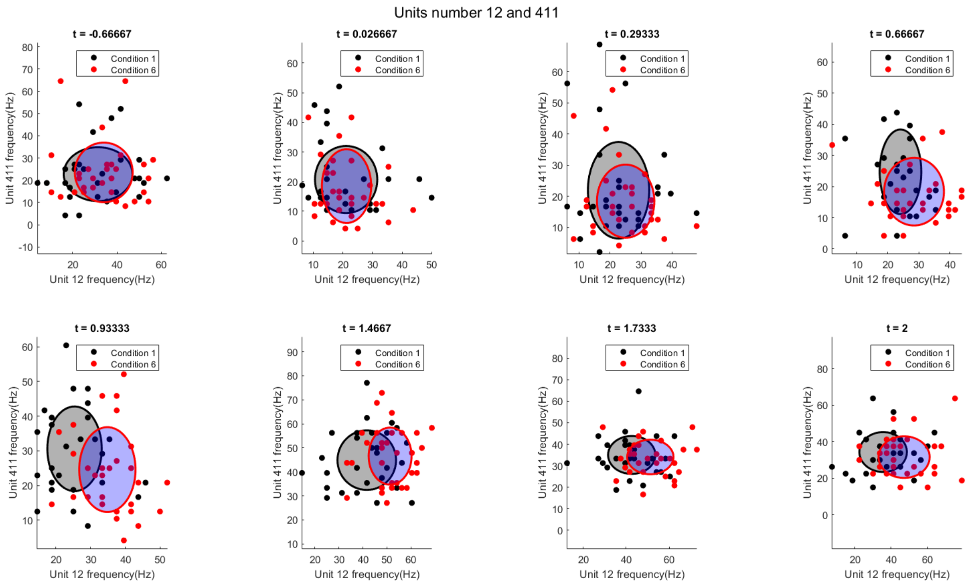

Figure 10: $t = 0$ is the stimuli onset

As can be seen from the plots, after the stimuli onset, the std rises in the x axis and ellipses start to get away from each other. This means that it is possible to understand some dynamics from the single units. Actually the ellipses are pretty distinguishable in figure 10. But there are also times that this is not the case like figure 11. In this figure, both units act similarly so the ellipses are indisguinshable and population analysis could be a better option. One thing to discuss is that I believe the reason that in figure 10 we have a good plot is that unit 12 shows a lot of change in conditions. (It has the lowest p-value in table 1) But yet there are also plots for other units that we have distinguishable ellipses but not as much as plots with unit 12 as one side. (figure 12)

In the end we want to suggest that the population analysis could be more effective than single unit analysis.

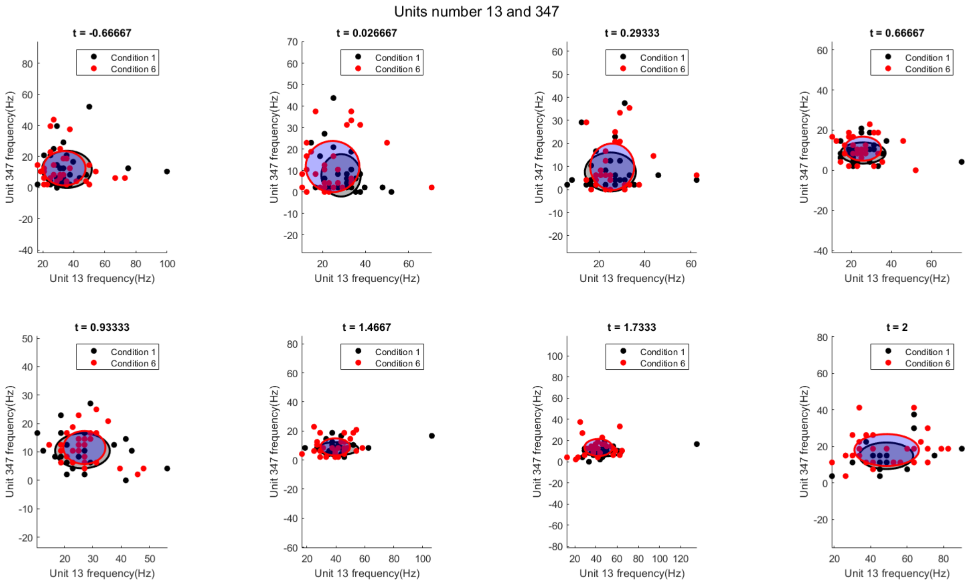

Figure 11: $t = 0$ is the stimuli onset

There are changes in mean and std of units in figure 11 but both units change in a similar manner so they are not distinguishable. In figure 12 around $t = 1.5ms$ we have distinguishable pattern but yet they have a large overlap.

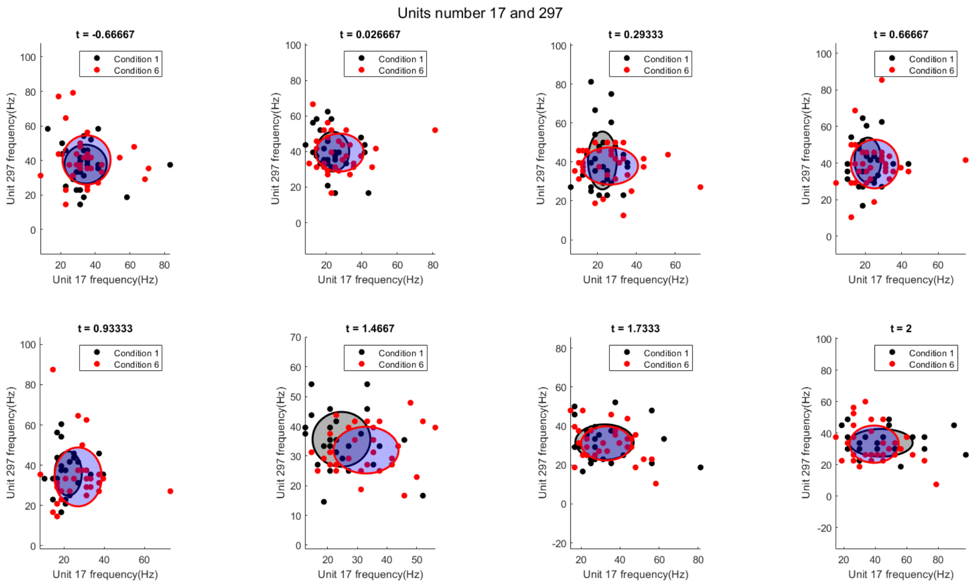

Figure 12: $t = 0$ is the stimuli onset

Step 3 - Population Analysis

In order to see the effect of the coditions on the population dynamics we use PCA to reduce the dimentionality to 2 or 3. Becuase PCA captures all kinds of variability and in order to reduce the effect of noise variability on the output, The time signal is averaged over trials of each condition so the variability would rely mostly on the firing dynamics itself. Also the firing rate was looked at after the stimuli onset.

Figure 13 shows the reduced dimension plots. The direction of time is shown using red arrows on the plot. As apparent from the plots for different condiotions, they start from around the same point and after some time, they start to move to another direction. the end points are in different state for each condition.

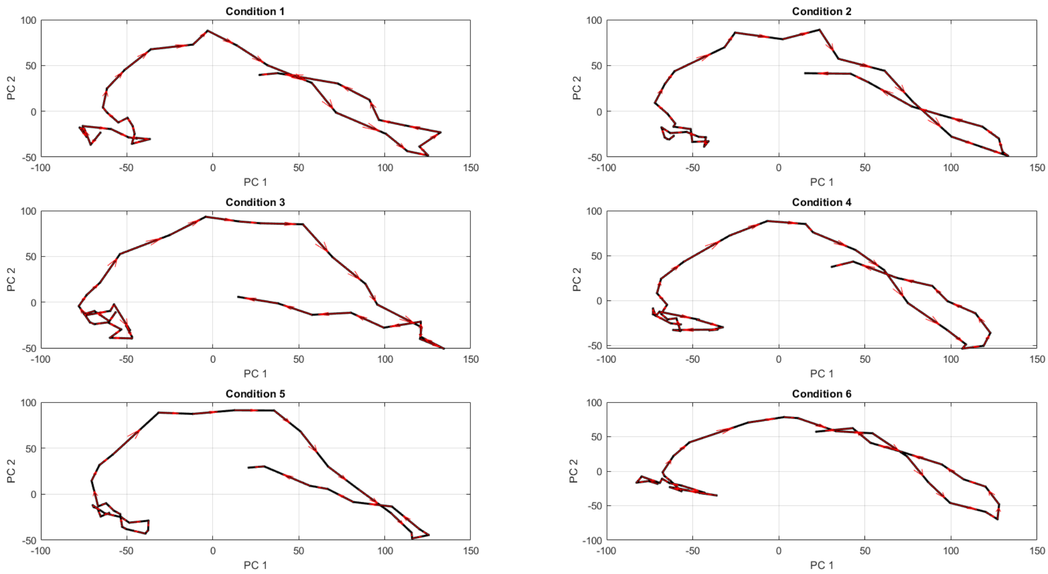

Figure 13: PCA plots for each condition

The 2D plot of all the conditions are brought together in figure 14. The different end points can be seen here.

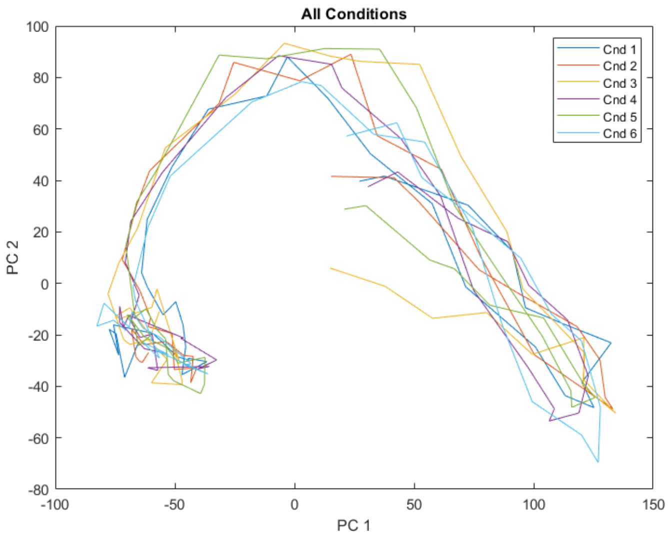

Figure 14: PCA plot for all conditions

As also the principal component 3 had a large eigen value, we check if there is another underlying dynamic that can not be seen in figure 14. In figure 15 we add the third component. As can be seen in the figure, although in 2 dimensions the end points seemed to be ending up in the same area but here we see that they are not actually in the same area in 3 dimensions an they are pretty apart from each other. The black lines are conditions number 3 and 5 and the red lines are conditions 4 and 6. (Condition 2 ended up near condition 3 and 5)

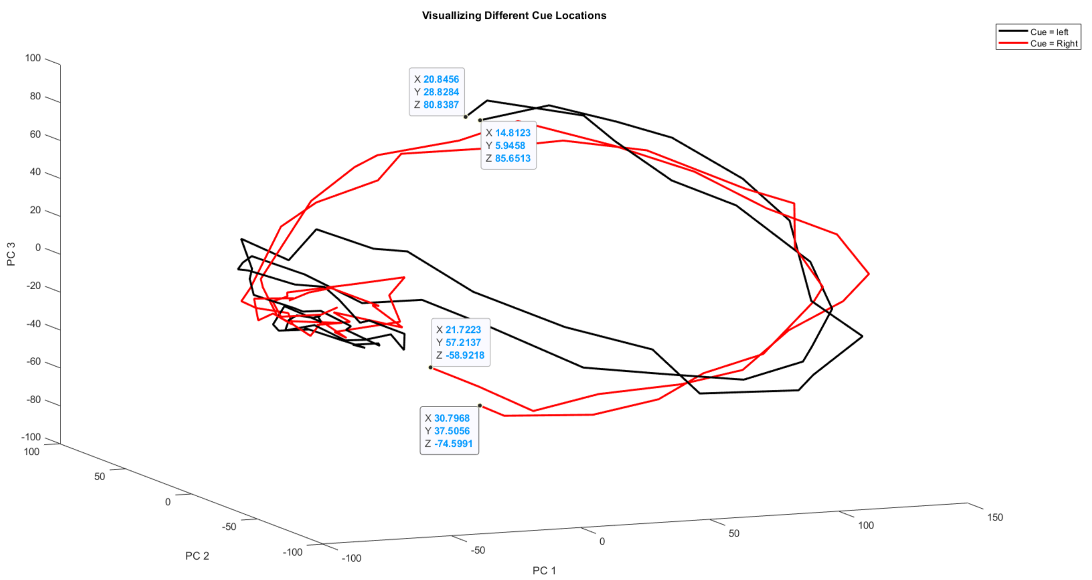

Figure 15: PCA plots for different cue locations

In figure 16 the mentioned dynamic can be seen becuase we replaced PC2 with PC3.

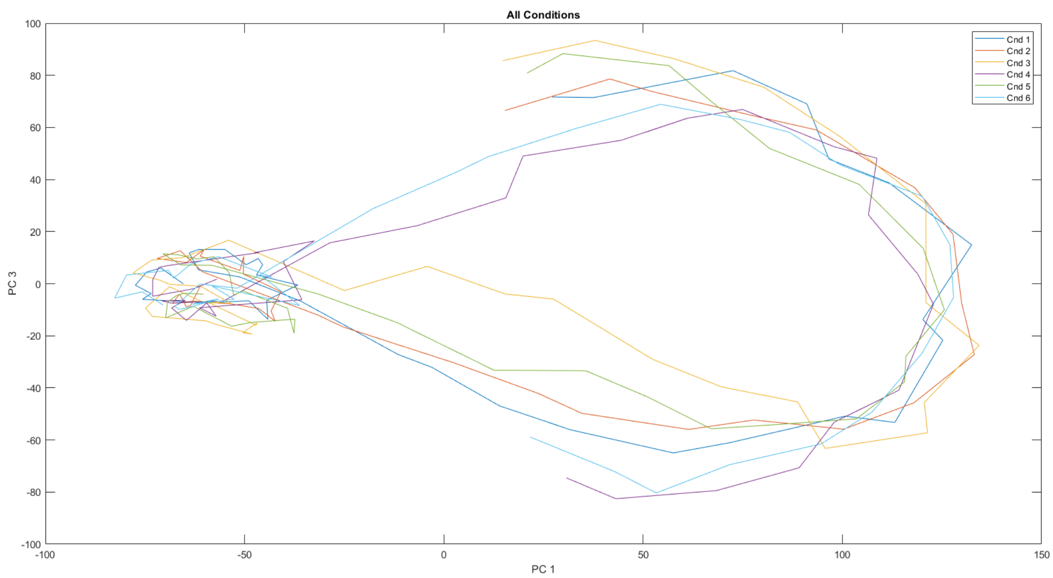

Figure 16: PCA plots for each condition

As a conclusion from the PCA we have seen much more encoding of the parameters. By plotting different PCs with respect to each other, we can see encoding of different condition parameters. e.g. some times the conditions with same cue end up in the same end point and a similar thing happens to expected reward parameter.

Step 4 - Shuffling

In this section, three methods of shuffling is applied to the data and for each shuffling method, the same proccessing as last step is done. The first method is just simply swapping the trials of each unit randomly with each other in a manner that the conditions are not real any more and the conditions labels will be totally random.

Approach 1

Figure 17 is the same plot as figure 13. The plots are not very different from the not shuffled data. Both shapes and directions are similar in both plots.

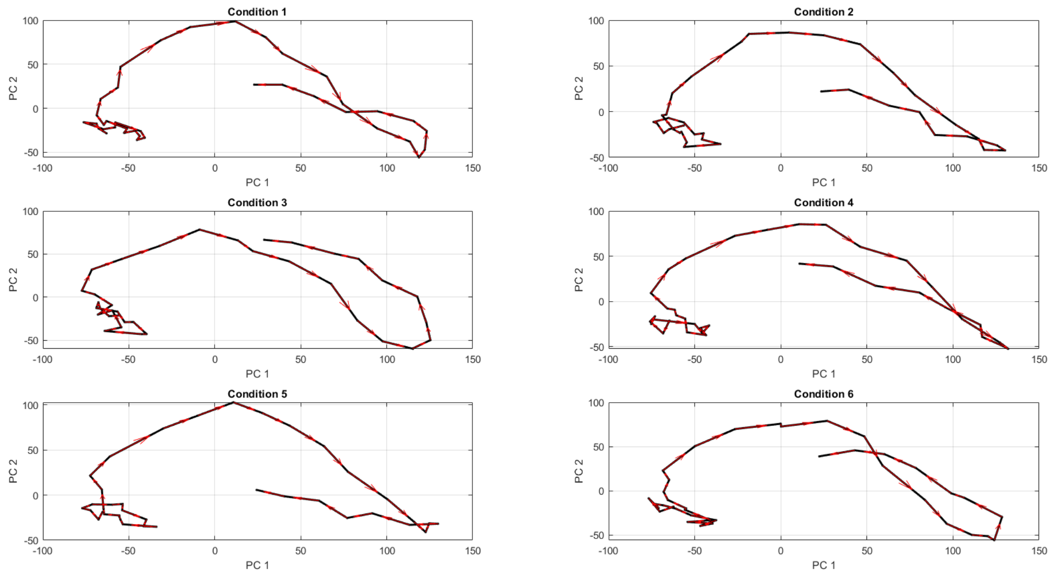

Figure 17: Suffled data PCA plots for each condition

Figure 18 is also similar to the same plot in last step.

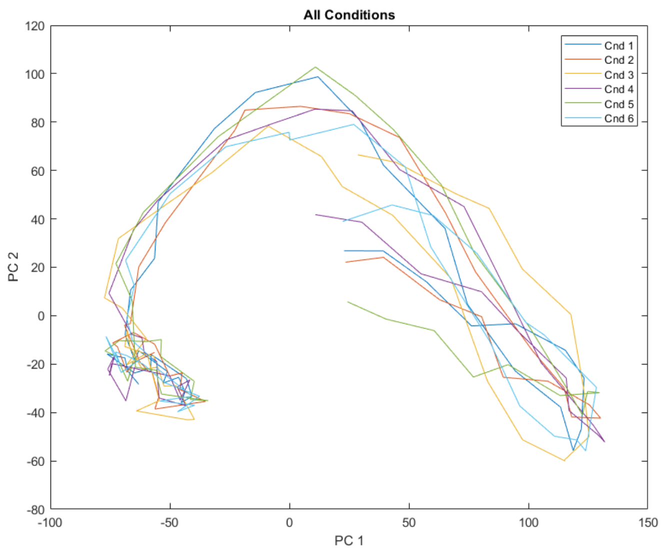

Figure 18: Suffled data PCA plot for all conditions

But an interesting plot can bee seen in figure 19. As can be seen in the figure the cue locations is not encoded here. So the first effect of shuffling is that the encoding is gone.

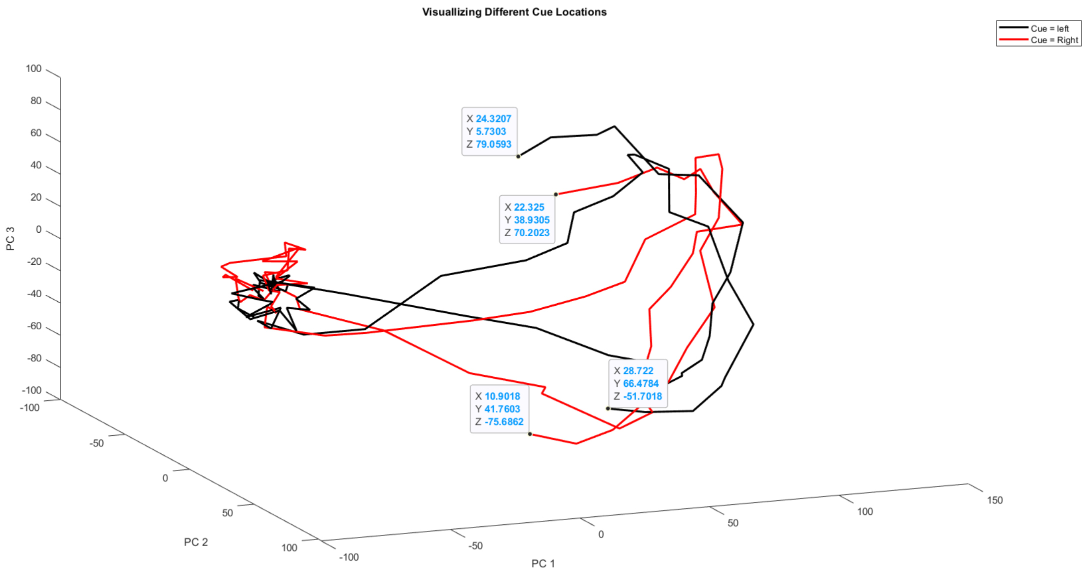

Figure 19: Suffled data PCA plots for different cue locations

Also in figure 20, conditions 2,5,6 ended up in top and conditions 1,3,4 ended up in bottom. This is also a sign of bad encoding of the data.

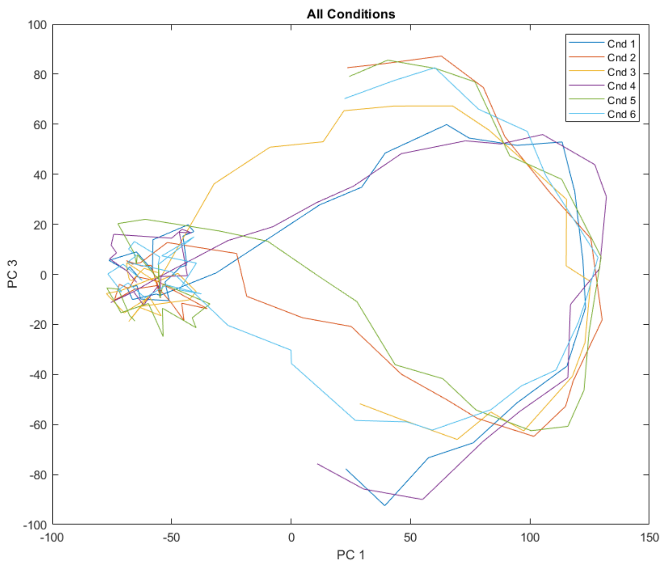

Figure 20: Suffled data PCA plots for each condition

In conclusion, the shiffling approach one looks kind of similar to the original data but there is a lack of encoding here. So we can understand there was a connection between the conditions and figures.

Approach 2 - CFR

The CFR method is applied to the data by modifying the MATLAB code that is available in the authors' github. All the same figure from last parts are brought here for comparison. As can be seen from the plots, the rotation dynamic is still there but it seems like the encoding is gone. So it makes it seems like that the unshuffled data actually showed a real dynamic which was raised by population activity and neural connections. But actually the rotation of the data may say that it does not rely on conditions and caused by the nature of the task.

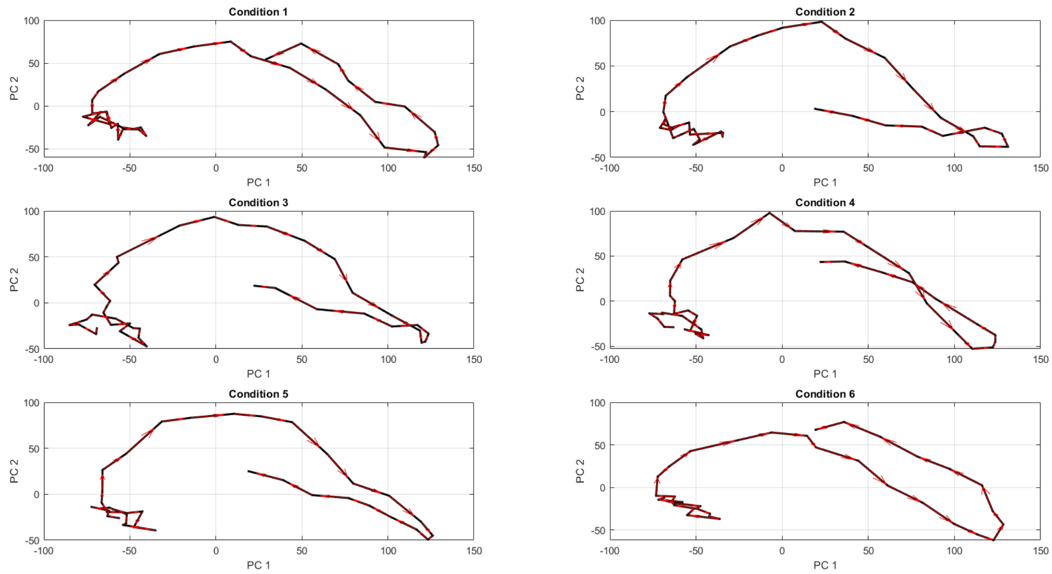

Figure 21: Suffled data PCA plots for each condition

Do not try to run the "CFR Data PCA" section in the code because whether you are gonna need the CFR shuffled data or you have to run the CFR section which will take about 15 minutes to run completely.

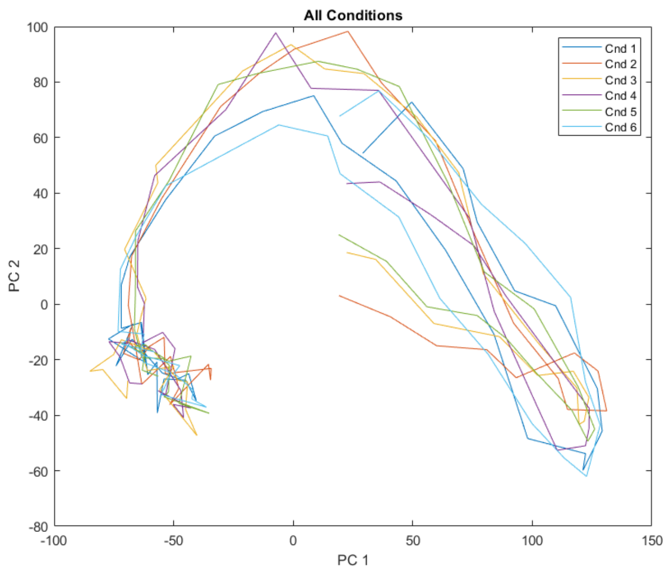

Figure 22: Suffled data PCA plot for all conditions

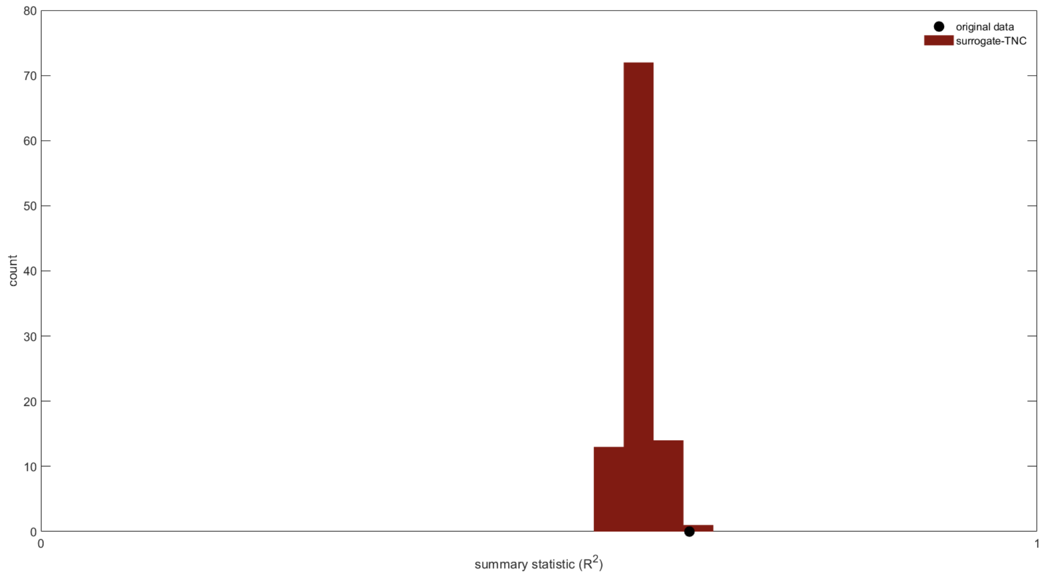

Figure 23: Significance of data

Figure 23 shows the significance of the data.

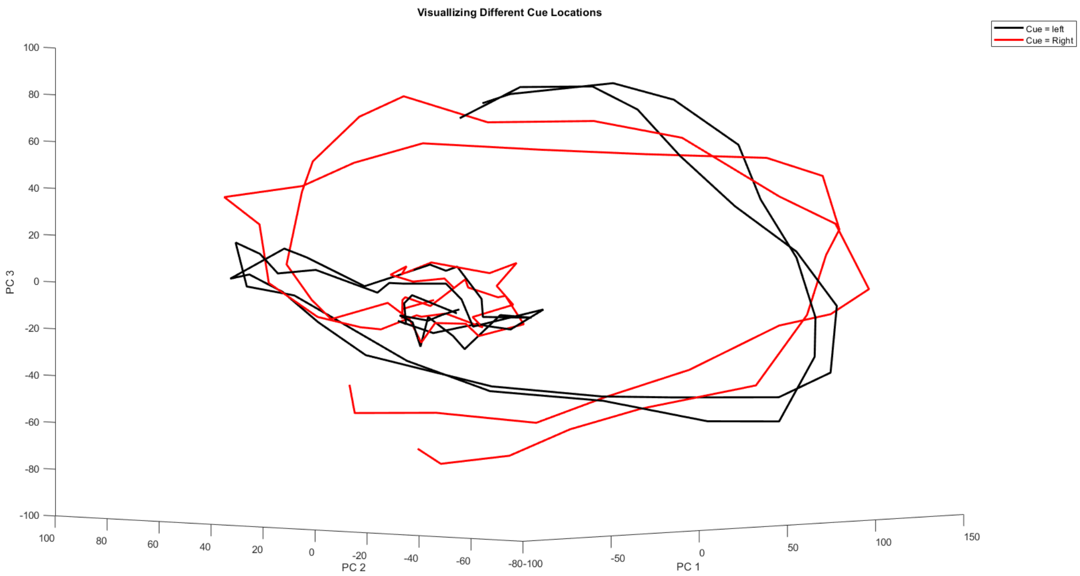

Figure 24: Suffled data PCA plots for different cue locations

It looks like that no encoding can be seen in the figures and there is no sign of classification dynamics for conditions.

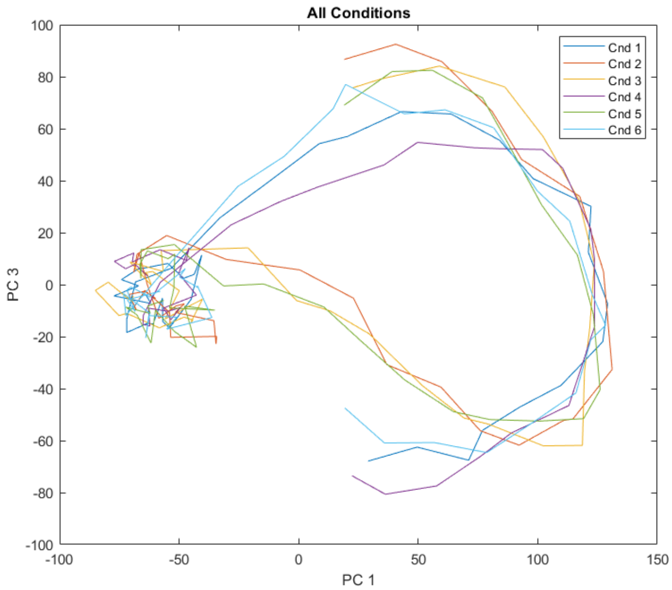

Figure 25: Suffled data PCA plots for each condition

As a conclusion the rotation is caused by the nature of task and the shuffled data still has the rotation property but the encoding of the task parameters is gone. Also we do the same we have done here using TME algorithm in the next part.

Approach 3 - TME

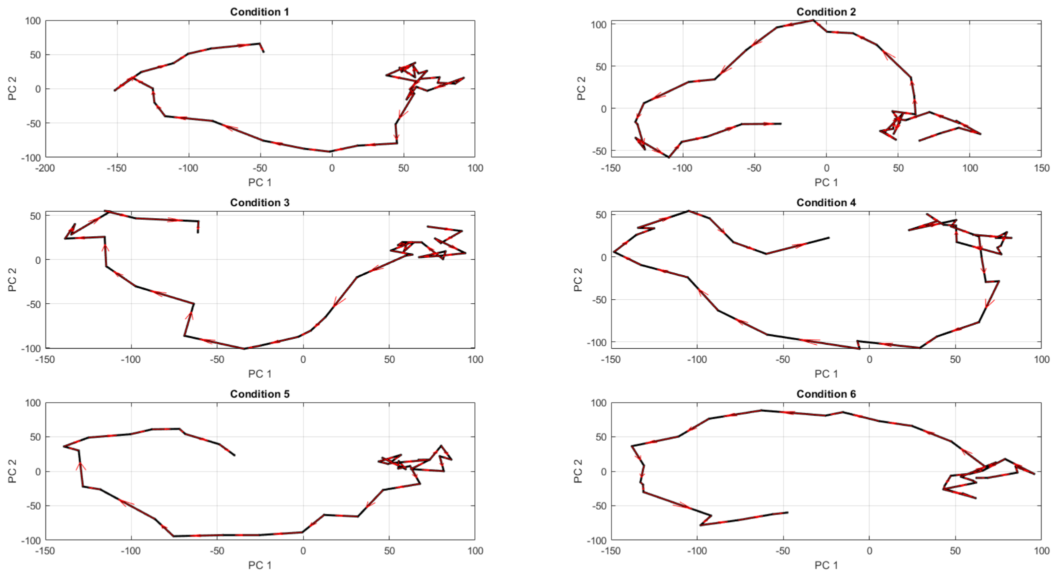

Figure 26: Suffled data PCA plots for each condition

It may seem that there is again a rotation in the data just like we saw in approach two. So we again see that by shuffling the data, the dynamics will be there. It again suggests an underlying dynamic in the neural activity in this specific task that leads to rotation.

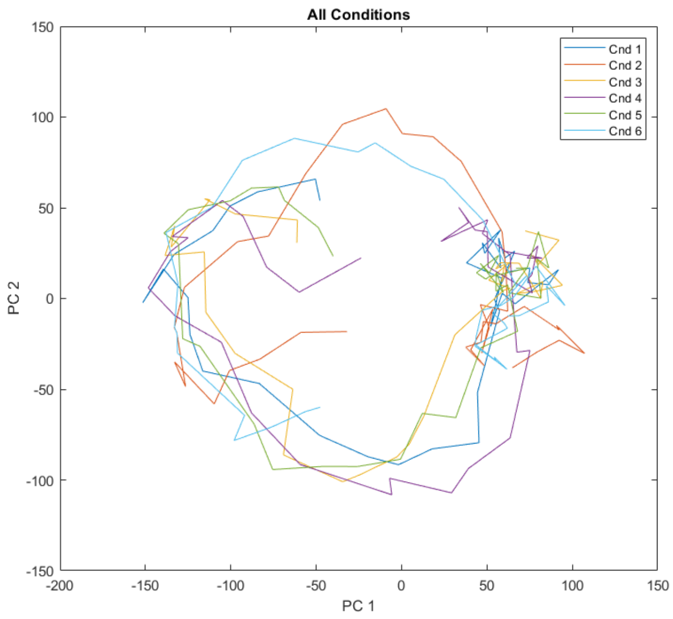

Figure 27: Suffled data PCA plot for all conditions

Figure 28 shows the significance of the data. As apparent from the figure, the original data lays far away from the shuffled data and it shows the significance of data before the shuffling.

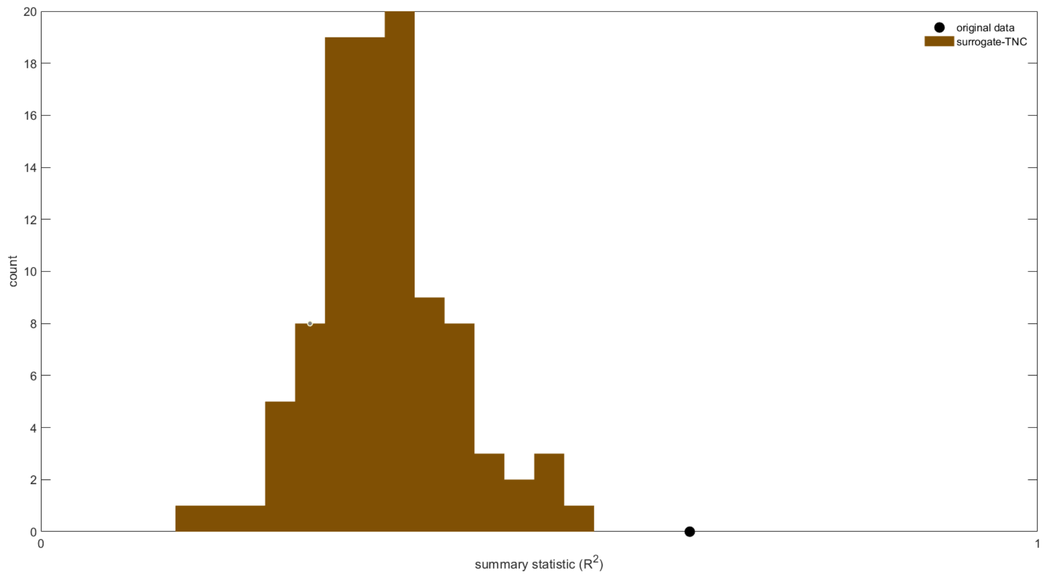

Figure 28: Significance of data

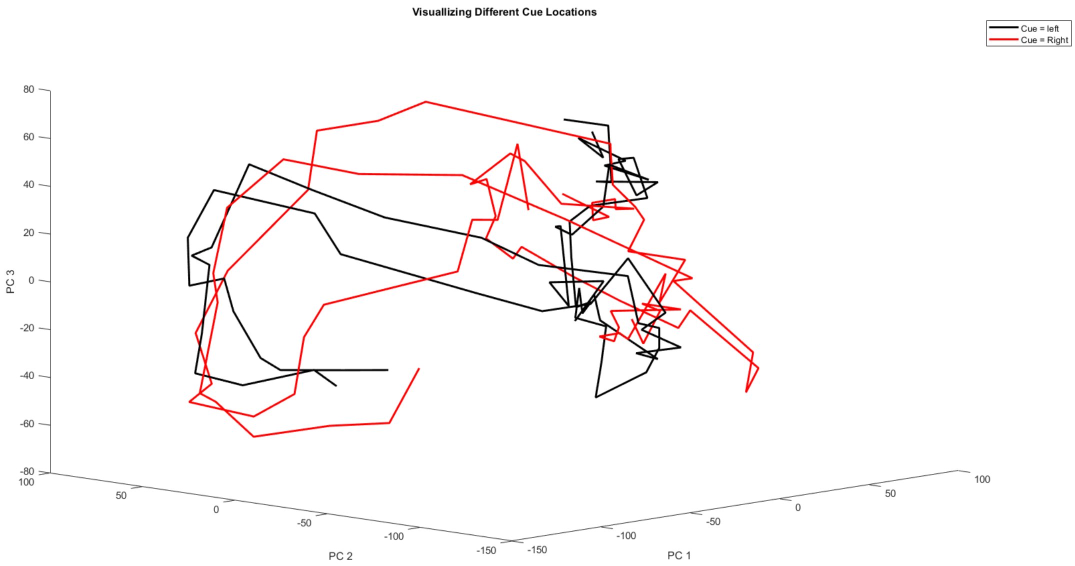

Figure 29: Suffled data PCA plots for different cue locations

As we saw earlier, the encoding of the task parameters is gone again.

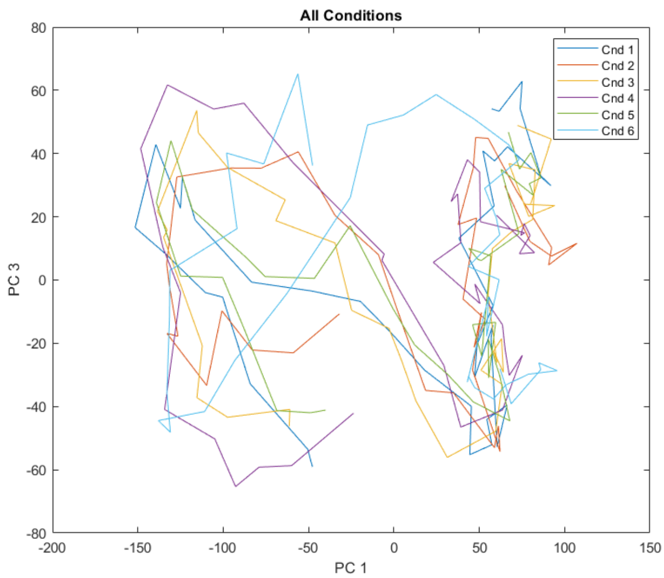

Figure 30: Suffled data PCA plots for each condition

In the end we have proven that the rotation dynamics has been rised from the neural population activity and that the plots in step 3 imply there is an encoding of the different task parameters including different rewards and cue locations.