LSD Hallucinogenic Effects In Network Attractor Dynamics

LSD may cause neurons to oscillate more asynchronously among possible attractor steady states

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Background:

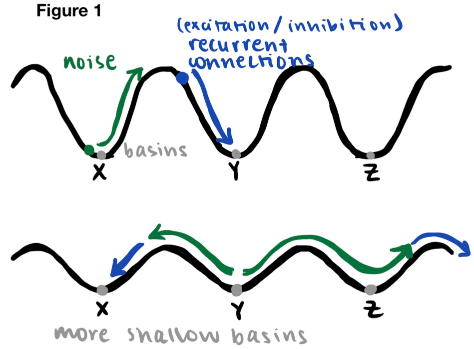
LSD, or lysergic acid diethylamide, is a synthetic chemical belonging to a group of drugs called psychedelics and is known to induce alterations in perception and thought. Larger doses also produce hallucinations and distortions of space and time (Iaria et al., 2010). This could occur as sensations or images seeming real even when they are not. Visual hallucinations are some of the most common, and are defined by perceptions of nonexistent objects, details or people. The neural basis of these hallucinations rests in the chemical compound binding to serotonin 2A receptors, resulting in their agonistic effects on the brain. Beyond observed patterns of oscillations and the impact on overall inhibition, neural bases of hallucinations are poorly understood (Iaria et al., 2010).

Attractor dynamics are important in understanding the effects of LSD on the brain. These can be described as networks starting in different states of activity and falling into a common attractor state. An attractor state represents a more stable interpretation of an ambiguous input pattern. So when an input pattern is presented, multiple constraints in patterns of activation can be satisfied and the network would fall into a harmonious representation. The bidirectional excitation disambiguates the input by gravitating into a stable pattern of activity (at the attractor basin), enforced by recurrent connections. It then makes sense that top-down semantic knowledge can strengthen the pull of these basins, helping attractor dynamics converge on an interpretation of an input.

The "stickiness" or pulling force of an attractor state depends on many factors. Noise is an important one in that it influences decision making, and pulls the network from one attractor basin to another. If a needed representation is in attractor Y but the network is currently in the attractor X basin, noise is the push that urges the necessary exploration. Inhibition and excitation patterns work to support the strength of the recurrent networks in attractors, influencing how strongly they stick to the basin.

LSD plays into this idea of attractor dynamics by providing the necessary noise and changes in inhibition to push the neural networks' representation out of one attractor dynamic into another. This is not always warranted however, because of the unnaturally high levels of noise and inhibition now introduced into the network, the basins become *theoretically* shallower. This, in turn, makes it easier to switch from one representation to another, and to switch to the incorrect representation and hallucinate (figure 1).

Figure 1



LSD and related hallucinogenic drugs have been researched in this context using face categorization tasks, and we hope to contribute to this body of literature as well as the greater topic of attractor dynamics and their relevance in neural networks (Iaria et al., 2009). Our primary aim is to replicate and observe the effects of LSD on neural networks in the context of face categorization tasks. We also aim to simulate the impact on the hallucinogenic effect when employing top-down input in our network. Lastly, we hope to explore whether literature on hallucinogens could be replicated in the computational domain.

One of the topics we hope to explore is discussed by Iaria et al., in investigating the effects of LSD after different amounts of time to deliberate on a task. Findings from several sub-studies have found that longer deliberation time leads to more incorrect responses as a result of more severe hallucinations (Iaria et al., 2010). Another topic worth looking into is LSD's impact on social cognition by targeting emotional facial recognition.

A review by Rocha et al. claimed that LSD reduces the recognition and categorization of negative emotions when presented with neutral or emotional faces (Rocha et., 2010). This implies that emotion is especially situated in the impact that LSD has on face perception. We hope to test claims concerning emotion-specific recognition deficits in the current study.

Lastly, a paper by Caputo puts forth the “Strange-Face-In-The-Mirror” illusion. According to his work, a participant not under the effect of a psychoactive substance, asked to maintain eye contact with themselves for approximately 10 minutes in a dim environment will begin to hallucinate. This leads him to conclude that hallucinogenic drugs are not the only way to induce visual hallucinations. We hope to apply these findings to the current paper in exploring if it is possible to replicate non-LSD induced hallucinations in the network by simply giving it more time to observe the presented faces.

We would also like to explore the impact of both bottom-up processing from face image to categories, and top-down processing from category values to face images (mental imagery) on modeling the hallucinogenic effect. In a paper exploring the relation between hallucinations and bidirectional connectivity, Aleman et. al claim that “hallucinations are caused by an imbalance between top-down influences and bottom-up processing.” We would like to test this claim by considering whether hallucinations are more likely to be driven by top-down or bottom-up input. Information in our model can flow in two directions and since these connections are roughly symmetric, the top down neurons can go back to the same neurons that project to them in the first place and activity can actually propagate from the higher level to the lower level. Top-down processing involves activating a set of high level category values, allowing the information flow down to the input layer, and producing an image that matches the representation of those category values. By using top-down input, you can ‘see’ or ‘imagine’ a face in the sense that your visual areas that represent the constituent features that represent that face as though they received inputs from the external environment instead of your thoughts. An example of replicating a hallucination driven by top-down input would be if we activate the category values associated with a specific face and the network responds by instead “imagining” someone else’s face, producing a distorted or incorrect image. We hypothesize that providing top-down input to the network from higher-category values would reduce the hallucinogenic effect we are attempting to model by increasing the ability of the network to activate the correct face represented by those values.

We would further like to understand the impact of two different ‘clamping’ conditions. The initial condition of top-down input we explore uses default ‘Hard’ clamping which first forces each layer to activate whichever pattern we want it to 'think about', and that then provides input to the input layer to activate. However, in order to allow the network to transition better between attractor states, we need the clamping to be more ‘soft’. This means we want to encourage the network to activate one of those patterns but then allow those units to still react to the reciprocal bottom up inputs in a dynamic way. We explore the impact of modifying the degree of intensity of clamping on LSD’s hallucinogenic effect on neural networks in the context of face categorization tasks.

We have identified the following hypotheses:

1) That the computational network under the simulated effects of LSD will exhibit difficulty in categorizing face identity, gender, and emotion when prompted with a face categorization task.

2) That these effects will create rapid switches in face perception, meaning the theoretical attractor basins have, in fact, gotten shallower.
3) That there is a leniency towards recognizing and hallucinating happy emotions.
4) That it is possible to achieve hallucinations in all modalities of categorization at the same time. (Ie. The network identifies an incorrect identity, emotion, and gender when presented with a face).
5) Time has an effect on the extent of hallucination persistence, and longer deliberation leads to more incorrect representations being outputted.
6) Providing the network with top-down input from higher-category values reduces the instances of hallucinations.
7) Decreasing the intensity of clamping when employing top-down input will increase the hallucinogenic effect.

We also recognize the lack of ecological validity in testing the effects of hallucinogenic drugs on a computational network. We intend to mitigate the extent of the hallucinations by varying levels of noise, inhibition, and rate of spike rate adaptation - which would be difficult to replicate in the dosing of a human participant with LSD.

Methods

The Model

To construct a neural network that can be reflective of the hallucinogenic effects of LSD, we employed a modified version of the face categorization simulation. The face categorization simulation explores the categorization of sensory inputs (here, simple faces) in different ways, retaining relevant information and collapsing across irrelevant information. In terms of attractor dynamics, in the model each input face and associated category forms a coordinated attractor.

The network settles on a specific attractor through the process of activation updating over cycles. The resulting attractor that the network settles on (from a particular input pattern) lies within its general attractor basin. So the task tests how smoothly a network can fall into one basin or unnecessarily switch to another by seeing things that are not there - or hallucinating. The modification to the default face categorization model was in a change of the code containing the NCycles parameter. We included this parameter to let the network deliberate - and hopefully, eventually hallucinate in a trial before having to give an answer.

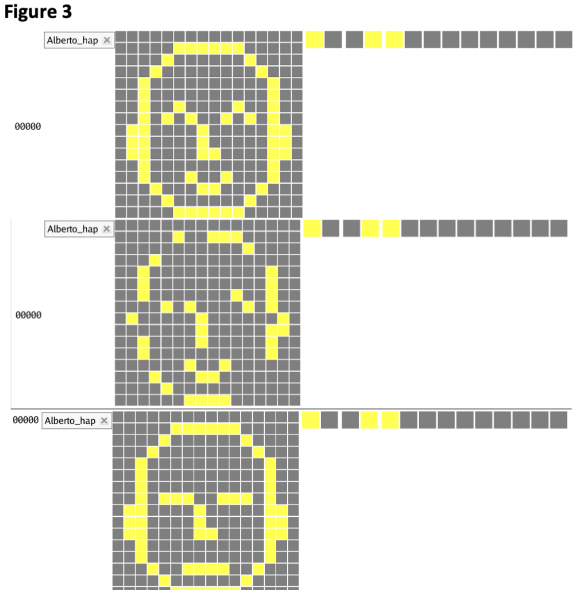
Figure 2

The network has an input layer, and three output layers representing different ways to categorize a face. These are the identity layer, corresponding to the identifiers of each input face, the emotion layer with a happy and sad binary, and a gender layer with a male and female binary (figure 2).

The Datasets

We presented the network with 3 datasets of inputs. The first included input patterns corresponding to full faces of a set of generated people (eg. Alberto, sad, male). The second was the same dataset but with incomplete versions of the faces, where 20 pixels are removed from the original face pattern. The third was emotionless faces with

Figure 3



neutral emotion identifiers (eyes/mouth). A sample of a full, partial, and emotionless face input is seen in figure 3.

Data collection

In each trial of full and partial face categorization, we recorded the number of times the network identified the wrong identity when trying to categorize the correct one. This meant presenting the network with a trial face and allowing it to deliberate - then using the VCR buttons to run through the trial and count how many times it settled on an incorrect category node (identity, face, or gender). The result is counter tables aimed to show how unstable attractor dynamics for each presented face are - in showing how "easy" it is to switch identities when presented with a face. If the network switches in one of the categories X number of times, this is a reflection of how shallow the attractor basins are as a result of some external influence (here, LSD) - and is representative of visual hallucinations. The counter tables come in modified ways but inherently keep track of how many "hallucinations" occur in each trial.

Parameters

In order to induce these hallucinations in a neural network, we attempt to model the biological effects of LSD by modifying the following four parameters in our network:

Inhibition: LSD administration impairs inhibitory performance and reduces brain activation (Schmidt et al., 2017). To model this effect, we alter inhibition in the network by lowering it from the default values in each layer to a range of values from (0.5 - 3).

Noise: LSD provides every neuron with some synaptic input that it doesn't normally get, this is done in the form of Noise. Noise added to the membrane potential plays an important role in attractor dynamics, since when the Network is stuck between attractor states, noise helps pull the network from one attractor basin to another. To model this effect, we change the Noise condition from the default ‘NoNoise’ to ‘GeNoise’. In order to replicate variation in Noise across neurons, we set Variance to 0.05.

Ncycles: We want to give the Network more time to hallucinate before it settles on an answer. To replicate this, we change Ncycles from the default 10 to range of values from (50-200). Then later up to 10000.

KNa: LSD administration tends to cause oscillations between the possible representations. Neurons/units that are activated for representation X eventually get fatigued, allowing the other competing units to become active. This process of neurons getting “tired” is called spike rate adaptation. In order to model this effect, we turn KNa ‘ON’ and set the rate of adaptation to 1 from the default 0.8 to increase the force of the effect.

Experimental Conditions

In order to replicate the hallucinogenic effect of LSD, we modify the above mentioned parameters across four different conditions before conducting further studies. Our goal is to find the optimal parameters that closely follow the neural basis of LSD to best model the effect.

Base Condition: This condition is meant to model baseline human performance on the face categorization task. Here, Input Layer inhibition is set at 2, KNa is Off, the NoNoise condition is used, and NCycles is set at 10. No additional modifications are made.

Condition 1: The Noise and Ncycles parameters are modified to simulate the hallucinogenic effects. The modifications made are:

- To provide every neuron with some synaptic input that it doesn’t get normally: set Set Noise to Ge Noise condition
- To include variation in noise across all neurons: set Noise Variation to 0.05

    - To give the Network more time to hallucinate before an answer is given: set Ncycles 100

<u>Condition 2: </u>The Inhibition and kNa parameters are modified to simulate the hallucinogenic effects. The modifications made are:

- To simulate spike rate adaptation: setKNaAdapt ON and Rate at 1
- To replicate inhibitory effect of LSD:
    - set Input Layer inhibition to 1.2 when KNa is OFF
    - set Input Layer inhibition to 0.8 when KNa is OFF

<u>Condition 3: </u>The Inhibition parameter is altered in other Layers to simulate the hallucinogenic effects. The modifications made are:

    - Set Emotion layer inhibition to 1.2
    - Set Gender layer inhibition to 1
    - Set Identity layer inhibition to 2.7

Aysha's Subproject:

<u>Condition 4: </u>Testing the effect of time (via. NCycles) on accuracy of output

- To test the impact of deliberation, NCycles was set to 50 - then to 300.
- Parameters from Condition 3 are replicated.

<u>Condition 5: </u>Replicating the findings from Rocha et al. (2009) with neutral face stimuli.

- To present the network with emotionless inputs, InputPats were changed to a specially created set of emotionless faces with altered eye and mouth shapes.
- Parameters from Condition 3 are replicated for optimal LSD induced hallucinations, as demonstrated by our findings.

Condition 6: Replicating the conditions described by Caputo (2010)

- To replicate the noise created by darkness in the experiment, set noise to GeNoise with Var=0.1. This creates an ambiguous input pattern
- To give the Network more time to hallucinate like in the experiment, NCycles at 10000

Areshva's Subproject:

Parameters:

Act.Clamp: We want to control whether we want to encourage the network to take one of the patterns top-down activated patterns but then allow those units to still react to the reciprocal bottom up inputs in a dynamic way, i.e, involve 'soft' clamping. This can be modified by setting the Act.Clamp to checked or unchecked

Gain (Act.Clamp Row):We want to control how strongly the patterns will be activated via soft clamping vs how much they would then react to their inputs. To replicate this, we can modify the Gain parameter in the Clamp row. Increasing the Gain value corresponds to making the clamping 'harder'

Condition 7: Testing whether hallucinations are more likely driven by top-down or bottom-up input:

- To allow input to the network to flow top-down from higher-level category values: modifying SetInput to include top-down input.
- To allow for 'hard" clamping: we check 'Hard' in the Act.Clamp row.
- Parameters from Condition 3 are replicated for optimal LSD induced hallucinations

Condition 8: Testing the impact of modifying the degree of intensity of clamping on LSD's hallucinogenic effect.

- To allow for 'soft' clamping: we uncheck 'Hard' in the Act.Clamp row.

- To increase the strength of pattern activation via soft clamping vs how much they would then react to their inputs: set Act.Clamp gain at default= 0.2
- Parameters from Condition 7 are replicated for optimal LSD induced hallucinations, driven by top-down, soft-clamped input.

Results

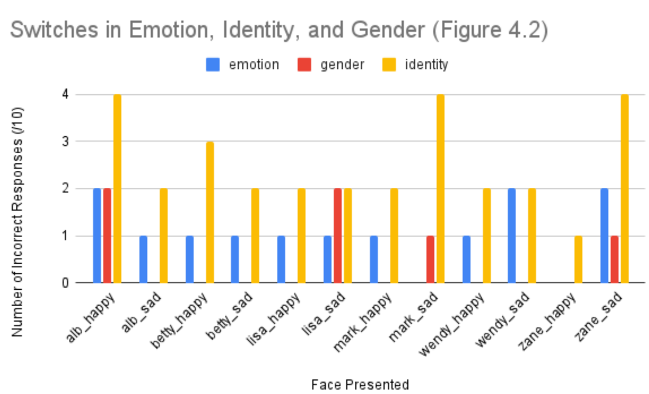
<u>Base Condition:</u> The network's performance was optimal, showing little to no oscillations in any layers. The network is immediately able to settle on a correct identity, gender, and emotion. This condition appears to be representative of baseline human performance.

figure 4.1

	number of incorrect responses, NCycles = 200		
	emotion	gender	identity
alb_happy	2	2	4
alb_sad	1		2
betty_happy	1		3
betty_sad	1		2
lisa_happy	1		2
lisa_sad	1	2	2
mark_happy	1		2
mark_sad		1	4
wendy_happy	1		2
wendy_sad	2		2
zane_happy			1
zane_sad	**2**	1	4

<u>Condition 1:</u> The network's performance is slightly hindered, showing some oscillations. Making these changes alone, we can see that the attractors are so strong that a little bit of noise does not hinder their self-reinforcing mechanism. The network is able to settle on a correct identity, gender, and emotion. The model does not yet replicate the hallucinogenic effect.

<u>Condition 2:</u> The network's performance is hindered, showing greater oscillations. Reducing inhibition and allowing the network to exhibit spike rate adaptation allowed the network to settle on the wrong identity node. The model replicates a mild hallucinogenic effect.



<u>Condition 3:</u> The network's performance is completely hindered. It oscillates frequently between different representations across all categories. The network frequently settles on

the wrong emotion, identity and gender. The model replicates the hallucinogenic effect to a great extent, and supports our hypothesis (1). The findings are shown in figure 4.1 (and visualized in 4.2), in a counter table averaged over 3 sets of trials, where each count represents the switch to an incorrect categorical node under the modified parameters.

Condition 4 (Aysha): With 10 trials, at NCycles = 300, the Network produced the correct output 62.9% of the time, with an average of 5.5 switches during deliberation. At NCycles = 50, the Network produced the correct output 39.2% of the time, with an average of 2.1 switches during deliberation. This provides evidence against my hypothesis (5) that longer deliberation periods lead to more incorrect outputs. However, more oscillations (or switches in identity) are observed when more time is given, even though they do not impact the final output of the network.

Condition 5 (Aysha): It was anticipated that given an emotionless face, the network would gravitate towards a "happy" representation over a "sad" one. The findings confirmed the hypothesis (3) (figure 5), and a happy output was produced given a neutral face 64% of the time across all trials.

figure 5

	average number of switches	happy output produced (out of 10)
alb_happy	3	3
alb_sad	2	7
betty_happy	0	9
betty_sad	2	6
lisa_happy	1	7
lisa_sad	1	6
mark_happy	0	10
mark_sad	2	6
wendy_happy	0	9
wendy_sad	4	2
zane_happy	0	8
zane_sad	3	4

Condition 6 (Aysha): In investigating Caputo's proposal of hallucinations in a network not affected by LSD over a large period of time, none of the input faces produced oscillations or switches in the 5000 NCycle timeframe. This provides evidence against my hypothesis that the illusion could be recreated with a neural network (4).

Condition 7

I explored the condition where I attempted using top-down input in the network, building off Condition 3. I hypothesized that when input to the network flows top down from higher category values, the network's ability to hallucinate will be greatly impaired. Hard clamping was used which allowed the network to 'imagine' a face entirely from input from the higher level information. Here, the model settled on the correct face 100% of the time, with 0 incorrect responses across all category values, a stark difference from the results of Condition 3 quantified in figure 4.1. These results support hypothesis (6) that hallucinations are more likely driven by top-down input.

<u>Condition 8 (Areshva)</u>

I also tested the impact of modifying the degree of intensity of clamping on LSD's hallucinogenic effect. Here, top-down input was turned on but 'soft' clamping was used to vary how strongly the patterns will be activated via top-down input vs how much they would then react to their inputs. The network more frequently than in Condition 3 (bottom-up processing only) settles on the wrong category values (identity, emotion and gender) and frequently hallucinates the wrong person when presented with a set of categories values representing a specific person. These results are quantified in Figure 6 and confirm the hypothesis (7) that decreasing the intensity of clamping when employing top-down input will increase the hallucinogenic effect.

figure 6

	number of incorrect responses, NCycles = 200		
	emotion	gender	identity
alb_happy	4	1	6
alb_sad	4		4
betty_happy	5	1	3
betty_sad	7	2	4
lisa_happy	4	2	2
lisa_sad		1	5
mark_happy	3	3	5
mark_sad	3		5
wendy_happy	5		4
wendy_sad	4	2	4
zane_happy		3	6
zane_sad	5	2	4

Conclusion

In the present study, we replicated the effects of LSD on a computational neural network. We explored alterations to noise, inhibition, and spike rate adaptation and achieved hallucinations while performing in a face categorization task. By first finding the optimal parameters to achieve dynamic hallucinations in the network, we were able to apply further changes to investigate both top down processing and extrapolate to test how adaptable the network is.

Areshva's subproject focused on the impact of using information from higher category values as input to the network (top-down) on LSD's hallucinogenic effect across different clamping conditions. The roughly symmetric bidirectional connections present in the network allow us to explore the impact of using top-down and bottom-up input on modeling the hallucinogenic effect. An example of replicating a hallucination in our network would be if we activate the category values of Alberto, Male, happy and the network responds by instead "imagining" what Wendy looks like when she is sad (Figure 7).

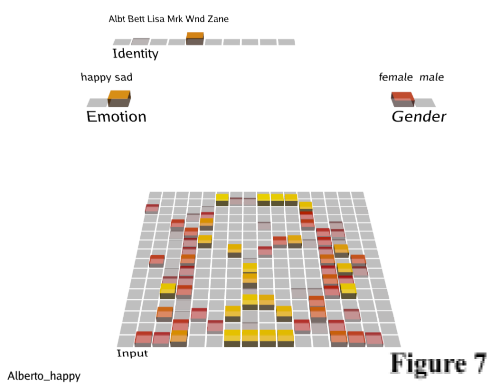


Figure 7

In terms of attractor dynamics, a coordinated attractor represents a specific face and its associated category values. The process of activation updating over cycles allows the network to settle into a specific attractor from a partial input pattern that nevertheless lies within its overall attractor basin. The benefit of bidirectional connectivity is the ability to fill in missing pieces of associated information, making it easier to settle into a specific attractor.

I provided the network with top-down input such that excitatory activity propagated directly from the higher to lower level. The network is able to 'imagine' a face in the sense that its lower level visual areas that represent that face's features from input received from its 'thoughts' as opposed to the external world. The 'hard' clamping essentially forces the network to activate for the face represented by the specific combination of category values we provide it as input. Because of this, despite the parameters replicating the effect of LSD (that allowed for hallucinations previously), the network is consistently able to settle on the right face.

To explore the effect of different intensity levels of clamping, I set the network's layers to 'soft' clamping. Following this, the face pattern comes into each input as an extra contribution to the excitatory net input, which is then integrated with the other synaptic inputs coming top-down from the category level. The network can still receive input from other neurons, reach membrane potential, and spike. We vary the amount of input the neurons receive from lower-level layers (from the external world, through the visual cortex) vs the amount it receives from higher level areas of the brain. Since we have already 'lesioned' the network by stimulating successful LSD induced hallucinations, the information it receives from the lower layers is incorrect in the sense that as additional bottom-up input to the network, the input face pattern does not correspond to the category values we provide as top-down input. This mis-match between top-down and bottom-up information is what causes the intensity of hallucinations we see in Condition 8, quantified in Figure 6. These findings confirm Aleman et al.'s claims and my hypothesis that decreasing the intensity of clamping when employing top-down input will increase the hallucinogenic effect.

Over Condition 7 and 8, we can conclude that hallucinations induced hallucinations are more likely not driven by top-down input but a mismatch between top-down and bottom-up information in the altered model. In the future it would be interesting to explore more complicated nuances of bidirectional connectivity and modeling hallucinations on distorted or incomplete faces. The impact of the altered parameters to stimulate the hallucinations on the ability of the network to first, successfully pattern complete using high and low level information and second, successfully activate the correct face across all three categories can be tested in our model by using a dataset of partially occluded face input images across Conditions 7 and 8.

Aysha's subproject expanded on modeling LSD by exploring how accurately our network can model human patterns of activity. We attempted to replicate findings in literature related to the deliberation time, the role of emotion recognition, and non-hallucinogenic hallucinations. Deliberation time was positively correlated with the number of correct outputs, but negatively correlated with the number of switches between identities during the deliberation period. This doesn't directly align with findings in literature as correct outputs have not been a metric for severity of hallucinations. However, the fact that at a longer deliberation time (NCycles=300), the network switched identities almost twice as much as in the shorter time (NCycles=50) speaks to the flattening of attractor dynamics if given the opportunity to deliberate without immediately producing a categorization response.

This is in line with conclusions drawn by Singleton et al., who claim that the serotonin receptors specific to LSD result in a flattening of the brain's energy dynamics (Singleton et al., 2021). This is what allows for "more facile and frequent state transitions" in the context of attractor dynamics - and explains the frequent switches in perceived identity. Figure 1 is applicable here in the more shallow depiction of attractor basins, as this is what the flattening of the neurological landscape would look like in a theoretical scope.

Our data also mirrored the claims in literature concerning recognition of positive emotions. The findings of happy emotions being more frequently identified in a condition with only neutral faces showed that the network was able to replicate human findings. These findings are explained by the modulation of activity by LSD in the amygdala, since this area is rich in 5-HT2A receptors (Rocha et al., 2019). The influence of the LSD on the network was strong enough to selectively target attractor dynamics relevant to emotional recognition and the drug's antidepressant properties contribute to the inhibition of negative emotion recognition, creating the leniency we observed in neutral faces (Rocha et al.. 2019). It is still fascinating that our model was able to demonstrate these effects since there was no specific activation of serotonin receptors - this is definitely something that we would look into given we had more time. We could do this by modeling a network that is linked to amygdala activity, wherein the inhibition would arise from 5-HT2A receptor activity specifically.

Our model no longer aligned with findings from the literature when we attempted to replicate the “Mirror in the face” illusion (Caputo, 2010). This was expected as Caputo employed a self-recognition task in making sober participants stare at themselves for prolonged periods of time. This could be what caused a discrepancy in our findings. Also, the change in noise in the model's parameters was not a replication of darkness as seen in Caputo’s study. A face is presented for extended periods of time, but is presented partially and with a significant amount of noise (since there is a lack of light). The brain attempts to compensate for the difficulty in binding traits that is created by dim lighting - leading to an inaccurate assembly of a warped face (Caputo, 2010). Expanding on the code to make noise more specific to this condition could be a possible way to mitigate this methodological flaw. There was a limit on how long deliberation could be in the computational model (<10,000) so this parameter could also be expanded upon further to test how long this sober hallucination would take.

We explored the idea that LSD causes neurons to oscillate more asynchronously among possible attractor steady states by modeling the hallucinogenic effect of the drug. We closely followed the neural basis of the drug across conditions by varying modifications to the parameters to best model the effects with the aim of contributing to the literature on stimulating the effects of hallucinogenic drugs in network attractor dynamics.

BIBLIOGRAPHY

Aleman, A., & Vercammen, A. (2013). The "bottom-up" and "top-down" components of the hallucinatory phenomenon. In R. Jardri, A. Cachia, P. Thomas, & D. Pins (Eds.), The neuroscience of hallucinations (pp. 107–121). Springer Science + Business Media. https://doi.org/10.1007/978-1-4614-4121-2_6

Caputo, G. B. (2010). Strange-face-in-the-mirror illusion. Perception, 39(7), 1007–1008. https://doi.org/10.1068/p6466

Iaria, G., Fox, C. J., Scheel, M., Stowe, R. M., & Barton, J. J. (2010). A case of persistent visual hallucinations of faces following LSD abuse: A functional magnetic resonance imaging study. Neurocase, 16(2), 106–118. https://doi.org/10.1080/13554790903329141

Rocha, J. M., Osório, F. L., Crippa, J. A., Bouso, J. C., Rossi, G. N., Hallak, J. E., & dos Santos, R. G. (2019). Serotonergic hallucinogens and recognition of facial emotion expressions: A systematic review of the literature. Therapeutic Advances in Psychopharmacology, 9, 204512531984577. https://doi.org/10.1177/2045125319845774

Schmidt, A., Müller, F., Lenz, C., Dolder, P. C., Schmid, Y., Zanchi, D., Lang, U. E., Liechti, M. E., & Borgwardt, S. (2017). Acute LSD effects on response inhibition neural networks. Psychological Medicine, 48(9), 1464–1473. https://doi.org/10.1017/s0033291717002914

Singleton, S. P., Luppi, A. I., Carhart-Harris, R. L., Cruzat, J., Roseman, L., Nutt, D. J., Deco, G., Kringelbach, M. L., Stamatakis, E. A., & Kuceyeski, A. (2021). LSD and psilocybin flatten the brain's energy landscape: Insights from receptor-informed network control theory. https://doi.org/10.1101/2021.05.14.444193