

## **Psychedelic drugs and motion vision: connectionist modeling using feedforward and recurrent networks**

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### **Abstract**

Psychedelic drugs have been found to result in errant recurrent excitation and dampened lateral inhibition throughout the central nervous system. A psychological manifestation of this network instability are hallucinations consisting of trailing afterimages during the perception of motion. To model the effects of psychedelic drugs on motion vision, three connectionist approaches were used. The experimental task was the prediction of a moving target's position one time-step in advance. Given that motion vision is mediated through recurrent neural networks, a biologically-constrained fully-recurrent network was developed for Experiment 1. However, this network failed to learn from the training sets, and performed poorly in experimental tasks. A simplified and less biologically-restricted version of the fully-recurrent network learnt successfully, with adequate performance and generalizability. In Experiment 2, a simple recurrent network was developed, resulting in similar performance but worse generalizability in comparison to Experiment 1. In Experiment 3, a standard feedforward network was developed. Network performance was excellent during training and when testing with the training set. However, the network was not generalizable; error increased with slight alterations in example sets. To represent the effects of psychedelics on these networks, inhibitory unit weights were reduced by 25% after training. This is meant to be analogous to psychedelic-induced reduction in lateral inhibition. Outputs characteristic of psychedelic hallucinations were elicited in the simplified fully-recurrent network in Experiment 1. Other than reduced performance, no discernable patterns were elicited from the simple recurrent and feedforward networks after weight manipulation.

## Introduction

Psychedelic drugs, such as psilocybin mushrooms and LSD, have been used by societies around the world since antiquity (Lee & Shlain 1992). This class of drugs is known for its ability to produce profoundly altered states of consciousness, with relatively minimal impact on basic faculties such as respiration and motor control. Recently, there has been a resurgence of interest in using these drugs to investigate and treat a variety of brain-related disorders, such as cluster headaches, depression, and PTSD. However, primarily due to legal restrictions, little is known about the neural mechanisms of these drugs despite encouraging evidence of their efficacy as pharmacotherapeutic agents. In recent years, neurobiological and neuroimaging research have made initial strides into elucidating the neural mechanisms of these drugs.

Psychedelic drugs are partial agonists of 5-HT<sub>2a</sub> receptors: excitatory G-protein coupled receptors commonly found in layer V of the neocortex (Forutan et al. 2002). 5-HT<sub>2a</sub> partial agonists have been shown to induce small asynchronous leakages of the excitatory transmitter glutamate, resulting in the amplification of intensity and duration of incoming stimuli, along with noise and artifacts (Aghajanian & Marek 1999; Ermentrout & Cowan 1979). Electrophysiological studies using psychedelic drugs have found that asynchronous glutamate release results in spontaneous post-synaptic currents (EPSCs). The pattern of EPSCs is reflective of the organization of the recurrent network they occur within, which is perhaps reflected in the character of the hallucinations seen under the influence of psychedelic drugs (Aghajanian et al. 1999). Psychedelics have also been found to dampen localized lateral inhibition throughout the nervous system, particularly in the sensory cortices (Lass et al. 1983). EPSCs may result in dampened lateral inhibition through overstimulation of inhibitory synapses across cortical columns (Shao & Burkhalter 1999).

The cellular and molecular effects of psychedelic drugs culminate in systems-level disruptions of neuronal activity. Functional neuroimaging studies have shown reduced cortical

functional connectivity when under the influence of psychedelic drugs, implying system-wide decoupling of various neural networks. Reduction of function connectivity is most significant in two major cortical “integration hubs;” the medial prefrontal cortex (mPFC) and the posterior cingulate cortex (PCC) (Carhard-Harris et al. 2012). Unsurprisingly, these two regions contain the highest densities of 5-HT<sub>2a</sub> receptors (Burnet et al. 1995). This reduction in functional connectivity seems somewhat paradoxical, given that psychedelics are known to result in recurrent overexcitation, at least at the micro-level. These two regions have some of the highest anatomical and functional connectivity to the rest of the nervous system. The mPFC is integral to attention and working memory, while the PCC is thought to mediate consciousness and awareness—all of these functions are significantly affected by psychedelic drugs (Buckner et al. 2008).

Hallucinations and other alterations in consciousness induced by psychedelics are thought occur via errant recurrent excitation of various processing pathways (Ermentrout & Cowan 1979; Gutkin et al. 1993). This is thought to disturb the finely-tuned temporal synchrony within and between these recurrent networks (Lumer et al. 1997). One example is the effects of psychedelics on motion vision. With sufficiently diminished thresholds for excitatory feedback and dampened lateral inhibition, the perception of motion results in a standing wave of recurrent excitation along the thalamocortical loop (Bressloff et al. 2001). This may be the cause of “motion-trails” and “ghosting” seen during the perception of motion while under the influence of psychedelic drugs (Contreras et al. 2007). If this mechanism is true, the time decay of these afterimages should be proportional to the intensity of feedback excitation, which is dependent on the receptor affinity



**Figure 1** – An example of a “motion trail” in the wake of a moving object. These types of hallucinations are characteristic of psychedelic drugs.

and plasma concentration of a psychedelic drug (Bressloff et al. 2001). The same general mechanism should hold true for other types of psychedelic hallucinations. In order to model the effects of psychedelic drugs on motion vision, a biologically-constrained fully-recurrent artificial neural network was developed. However, poor network performance led to the development of another (much simplified) fully-recurrent network, along with a simple recurrent network and a standard feedforward network.

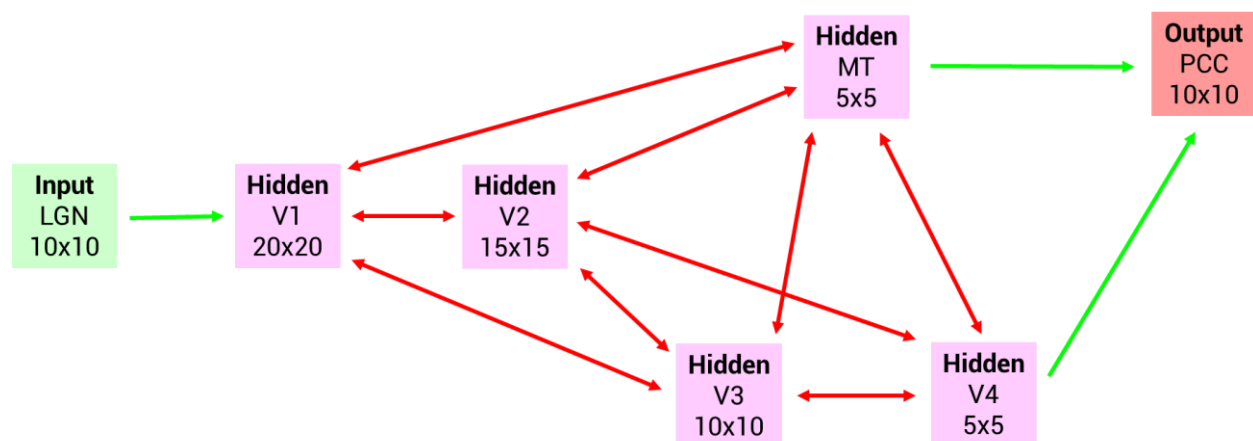
### **Experiment 1 – Fully Recurrent Networks**

When attempting to model motion vision through a parallel distributed processing framework, the use of a fully recurrent network seems like an obvious choice. Motion vision, like all other sensory processing, is mediated through recurrent neural networks. Fully recurrent networks use concurrent updates and back-propagate error through time. However, current computational techniques are not developed enough to simulate iterative sensory processing with realism. Considering these constraints, the aim is to develop a highly-simplified but still biologically-constrained computational model of motion vision using a fully recurrent network. In this experiment, the primary objective is for the network to predict (reconstruct) the position of a “moving” target at least one time-step in advance. The secondary objective is to simulate the effects of psychedelic drugs on motion vision; the perception of “trails” and “ghosting” that result from weakened lateral inhibition across the visual system. In this simulation, this would manifest as erroneous continued activation of units in the wake of the moving target.

#### *Materials and Methods*

This simulation is run on the LENS software package, a C-based neural network simulator. The input and output groups, meant to represent the LGN and PCC respectively, are composed of a 10x10 unit grid, serving as a two-dimensional space for movement to be simulated within. The hidden groups consist of the structures of the striate and extrastriate

cortex. The number of units within the hidden groups decreases with distance from the input group. This is meant to simulate the progressive diffusion of receptive fields from lower-level to higher-level sensory structures. Connectivity between the unit groups is a rough approximation of the anatomical connectivity between the cortical structures they represent. To “topographically” organize the network, group connections are fanned, meaning that maximum connectivity is found between similarly-positioned units in different groups, with the weakest connectivity between distantly-positioned units.



**Figure 2** – Network design in Experiment 1 (fully recurrent network). Each unit group is meant to represent a structure in the visual system. For biological realism, units are connected to each other topographically, and higher-level groups contain less units.

The moving target is represented as a single point of activation per time-step within the input group. To simulate movement, activation is shifted one adjacent unit with each time-step, in accordance to a predetermined trajectory. Movement is set at a constant speed (1 unit/time), with either a horizontal or vertical linear trajectory of varying length (3-10 units). Movement terminates once the moving target reaches the edge of the grid. Once terminated, another example is used, activating different units following a different trajectory. A total of 100 examples were used in the training set, with another 50 examples used in the testing set. Each example activates a single unit in the input group, and comes with a targeted unit in the output group, representing current and future (1 time-step) positions of the moving target respectively.

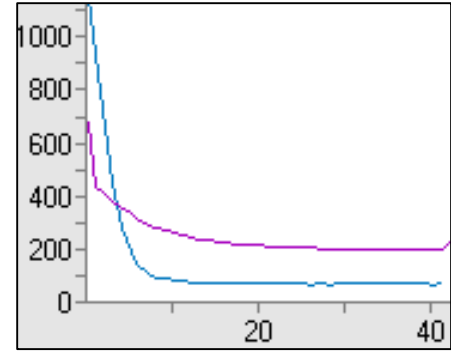
To successfully simulate movement, the network should activate the target unit in the output group in response to an input. After achieving sufficient performance in the primary task, the effects of psychedelics on the network will be examined. To simulate the effect of psychedelics on motion vision—reduction of lateral inhibition—negative unit weights will be reduced by 25% after sufficient training. Initial network parameters are as follows, and are used throughout Experiment 1 unless explicitly specified: input noise, randomized initial weights (range of -1 to 1); learning algorithm = Doug's Momentum; learning rate = 0.01; momentum = 0.9; weight decay = 0.0001; gain = 1.1, target radius = 0; error radius = 0; weight updates = 500; batch size = 10.

### *Results and Discussion*

The initial design of the fully-recurrent network (Figure 1) did not achieve learning. Hidden unit weights did not change with training, only becoming changing due to noise and decay rate. Outputs remained stable throughout training for all examples other than the variations induced by noise. A variety of different network parameters were used, but none were able to impact learning. To determine whether a fully recurrent network can learn the experimental task, a much simpler network was designed. In the new network, the last two hidden groups were eliminated, leaving only one 20x20 hidden group. Using the initial network parameters, learning was achieved. However, the marked drop in error rate seemed resultant of overtraining—outputs for each example remained the same, and the only units activated were ones included in the training set, with activation correlating to the frequency of activation in the training set. This suggests that the network was training for the aggregate inputs and targets in the training set, not optimizing for individual examples.

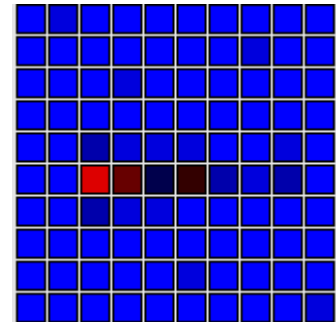
Using the simplified network, non-batched training produced more reasonable results; noticeable differences in network output between examples. Output activation was much less diffused, and was focused on the target unit. Furthermore, generalizability with the testing set

was much better than with batched learning. All of this indicates much improved network performance, but incredibly, the error rate is an order-of-magnitude higher compared to batched training. LENS documentation does not seem to mention the error rate algorithm used in the program, and the implications of this higher error rate is unknown.



**Figure 3** – Error rates of batched (purple) vs. non-batched (blue) training.

To simulate the effects of psychedelics on motion vision, inhibitory (negative) hidden unit weights from non-batched training were reduced by 25%. When testing with the testing set, performance was significantly reduced with no clear pattern. However, when testing with the training set, output activation was more diffused. Much more activation was seen in the units in the wake of the moving target, and somewhat more activation was seen in the units adjacent to the moving target. Interestingly, activation was not increased in the units in the path of the moving target. This pattern would likely have not been elicited if the groups were connected in a non-topographic fashion. However, this output pattern only occurred in units not used by other trajectories in the training set, presumably due to their influence on hidden unit weights.



**Figure 4** – A “motion trail” in the wake of a leftward-moving target.

In summary, the original “biologically constrained” fully-recurrent network failed to learn from the training set. A simplified version of the network *did* learn from the training set, but did so through aggregating data from all examples in the training set, thus compromising generalizability. Using non-batched training solved this problem and resulted in better performance and generalizability. However, much error was still seen, especially when using the testing set. Additionally, non-batched learning requires significantly more computational

resources, increasing the time needed for training and testing. Fully-recurrent networks have been shown to achieve robust performance in similar time-series based learning applications, and the performance seen in this experiment is likely not a result of the inherent properties of this network type (Connor et al. 1994). Since performance using fully-recurrent networks could be improved, a reasonable alternative would be to use simple recurrent networks.

## **Experiment 2 – Simple Recurrent Networks**

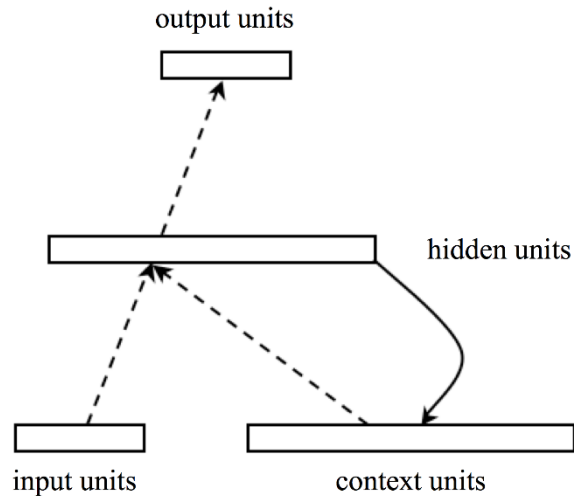
Simple recurrent networks differ from fully recurrent networks in that they function like standard feedforward networks, but have a context group(s) connected to each hidden group in order to provide limited temporal backpropagation. Context groups store the inputs of the hidden group from previous time-step(s). The number of context groups connected to a hidden group equals the number of previous time-steps that are stored. Fully-recurrent networks update all group inputs first before calculating group outputs. In contrast, simple recurrent and standard networks update inputs and outputs sequentially on a per-group basis (Elman 1991). Simple recurrent networks may provide better performance for motion-tracking tasks, as changes can be made to individual groups, not the entire network (Pearlmutter 1989). However, simple recurrent networks are much less biologically-realistic, as nearly all recurrent networks in the nervous system are continuous.

### *Materials and Methods*

The design of the simple recurrent network is very similar to that of the simplified version of the fully-recurrent network used in Experiment 1. The input and output groups consist of 10x10 unit arrays. The hidden layer consists of a 20x20 array, and is connected to three context groups. Three context groups were used to provide a storage capacity of three previous time-steps, improving overall network performance (Elman 1991). Between-group connectivity is “fanned” like the previous networks, in order to simulate topographical anatomical connectivity.



The training and testing sets used in Experiment 1 will also be used in this experiment. The primary objective also remains the same: predicting the location of a moving target one time-step in advance. After achieving sufficient performance in the primary task, the effects of psychedelics on the network will be examined. To simulate the effect of psychedelics on motion vision—



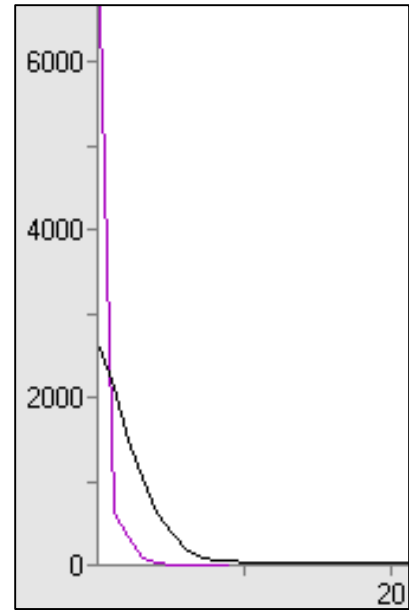
**Figure 5** – Diagram of a basic simple recurrent network.

reduction of lateral inhibition—negative unit weights will be reduced by 25% after sufficient training. Initial network parameters are as follows, and are used throughout the experiment unless explicitly specified: input noise; randomized initial weights (range of -1 to 1); learning algorithm = Doug's Momentum; learning rate = 0.01; momentum = 0.9; weight decay = 0.0001; gain = 1.1, target radius = 0; error radius = 0; weight updates = 500; batch size = 10.

### *Results and Discussion*

Using the initial network parameters, network output featured similar accuracy to the non-batch trained fully-recurrent network. Despite similar accuracy, the simple recurrent network featured lower levels of activation. Additionally, many extraneous units featured very small amounts of activation. However, the majority of activation was usually centered on the target units. Error rates were marginally better than that of the batch-trained fully-recurrent network, and much better than that of the non-batch trained fully-recurrent network. Generalizability was worse than that of the fully-recurrent network, as error rates when testing using the testing set were about 25% higher. Simple recurrent networks seem much more tolerant of batched training, as using it still resulted in decent performance, unlike with fully-recurrent networks.

While batched training did not result in reduced performance, non-batched learning still resulted in performance improvements. Using a learning rate of 0.1 and batch size of 0, network performance during training was improved by 50%. Output activation was much stronger ( $\sim 0.99$  on target output units) and less diffused, with accuracy better than all previous tests. However, generalization with the testing set was much worse, as the resulting error rate was double that seen with batched training. Tweaking of other network parameters, including additional noise, resulted in similar results. Thus, despite better performance during training, batched training is still a better choice due to its superior generalizability.



**Figure 6** – Error rates of batched (black) vs. non-batched (purple) training.

The weights produced from batched training were used in simulating the effect of psychedelics on motion vision. Inhibitory (negative) weights were reduced by 25% to simulate a reduction in lateral inhibition. When testing using the training set, a vaguely similar pattern to that of the fully-recurrent network was seen. However, like in the normal condition, output activation was much less strong and more diffused compared to the fully-recurrent network. Errant activation around the target output unit was also seen, but with a much broader reach than with the fully-recurrent network. Unlike the fully-recurrent network, errant activation was not focused in the wake of the moving target, instead being randomly distributed around the output target. This is not characteristic of the “motion trails” and “ghosting” seen under the influence of psychedelic drugs, they may be attributable to the reduced biological realism of simple recurrent networks. When testing using the testing set, performance was reduced significantly, but an overarching pattern was not discernable.

In summary, the use of batched training in this experiment's partial recurrent network resulted in marginally better performance than the non-batch trained fully-recurrent network, but had slightly worse generalizability. Non-batched training with the partial recurrent network resulted in very good performance when testing using the training set. However, generalizability was much worse than any previous test, despite added noise and changes in other parameters. This suggests that non-batched training learns specifically for the training set used, and is thus not generalizable—batch training is the best option. Since some aspects of network performance improved with a hybrid of feedforward and recurrent network properties, the use of a fully feedforward network may yield additional improvements.

### **Experiment 3 – Feedforward Networks**

Information in a feedforward network moves sequentially, with backpropagation occurring only on a per-group basis within each time-step. Therefore, there is no backpropagation through time. Feedforward networks are found within the nervous system, and sensory systems generally feature a mix of feedforward and recurrent circuits. However, motion vision seems to be mediated by recurrent processing, and thus the use of a feedforward network to simulate motion vision is not biologically realistic (Lamme & Roelfsema 2000). Despite the lack of biological realism, it would be interesting to see whether a standard feedforward network can predict motion trajectories.

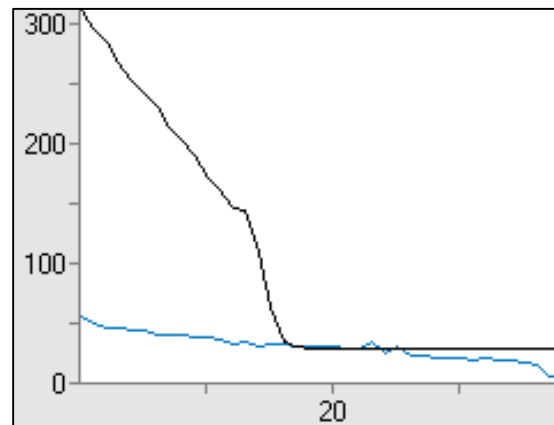
#### *Materials and Methods*

The design of the simple recurrent network is very similar to that of the simplified version of the fully-recurrent network used in Experiment 1. The network consists of three unit groups: input, output, and the hidden layer. Input and output groups consist of 10x10 unit array, while the hidden layer consists of a 20x20 unit array. The unit groups have fanned connectivity to remain consistent with the previous experiments, and to simulate topographical anatomical

connectivity. The training and testing sets used in Experiments 1 and 2 will also be used in this experiment. The primary objective also remains the same: predicting the location of a moving target one time-step in advance. After achieving sufficient performance in the primary task, the effects of psychedelics on the network will be examined. To simulate the effect of psychedelics on motion vision—reduction of lateral inhibition—negative unit weights will be reduced by 25% after sufficient training. Initial network parameters are as follows, and are used throughout the experiment unless explicitly specified: input noise; randomized initial weights (range of -1 to 1); learning algorithm = Doug's Momentum; learning rate = 0.1; momentum = 0.9; weight decay = 0.0001; gain = 1.1, target radius = 0; error radius = 0; weight updates = 500; batch size = 10.

### *Results and Discussion*

Using the initial parameters, the feedforward network achieved excellent performance. When testing the network using the training set, performance beat that of any other previous trial, with error nearly eliminated. Output pattern was similar to that of the non-batch trained simple recurrent network: little diffusion, with target output units having activations of over 0.9. However, when



**Figure 6** – Error rates of batched (blue) vs. non-batched (black) training.

testing using the testing set, error was much greater, with performance comparable to that of the batch-trained simple recurrent network. Thus, even though performance during training is exceptional, generalizability is fairly low. Tweaking of learning rate, gain, and momentum did not improve generalizability, suggesting that it is a stable feature in this network. The use of batched training did not seem to result in any performance decrements, unlike those seen with fully-recurrent networks.

Since generalizability could be further improved on, non-batched training was also used. Using all the same initial parameters except for a batch size of zero, network performance was significantly hampered compared to that of batch training, though still fairly good. For the training set, error rates were similar to that of the batch-trained simple recurrent network. However, the pattern of output activation was similar to that of the batch-trained feedforward network: little diffusion and strong target unit activation (when correct). When testing the network using the testing set, performance and error rate was similar to that seen with batch training. Thus, generalizability did not improve, and training performance actually worsened.

To simulate the effects of psychedelic drugs on motion vision, the weights produced from batch training were used, with inhibitory (negative) weights reduced by 25%. The reduced weights were loaded into LENS. When testing with the training set, performance was reduced significantly in comparison to the normal weights. However, no discernable pattern in the output could be found; there were only marginally activated units randomly dispersed throughout the output grid. When testing using the testing set, similar results were achieved. The lack of discernable patterns elicited are likely due to the differences between feedforward and recurrent networks.

While the feedforward network achieved exceptional performance when using the training set, performance using other testing sets left much to be desired. Despite the addition of noise and manipulation of other parameters, generalizability could not be improved. This may suggest that feedforward networks are not optimal for motion trajectory prediction, particularly due to its dependence on temporal information. This is likely the reason why motion vision is mediated by recurrent circuits in naturalistic settings, such as in the human central nervous system. Furthermore, previous attempts at computational motion trajectory prediction have used recurrent networks, not feedforward ones.

## Conclusion

The original “biologically constrained” fully-recurrent network in Experiment 1 failed to learn from the training set, likely due to its complexity. A simplified and less biologically-restricted version of the fully-recurrent network *did* learn from the training set, but did so through aggregating data from all examples in the training set, thus compromising generalizability. Using non-batch training solved this problem and resulted in better performance and generalizability. However, much error was still seen, especially when using the testing set. Furthermore, non-batch training requires significantly more computational resources and time, which is a significant detriment to its use. In Experiment 2, a simple recurrent network was used instead, and featured a similar design to the simplified fully-recurrent network, though with the addition of three context groups. Batch training with the simple recurrent network resulted in similar performance to that of non-batch trained fully-recurrent network, though with worse generalizability. Non-batch training of the simple recurrent network produced very good performance within the training set, but essentially had no generalizability beyond that. Even better performance within the training set was seen in the feedforward network used in Experiment 3. However, generalizability was very poor. Overall, despite its anomalously high error rate, the simplified fully-recurrent network resulted in the best motion vision performance. This may be attributable to the similarities between artificial and natural fully recurrent networks.

The secondary objective of these experiments is to recreate the network instability induced by psychedelic drugs, namely through the reduction of lateral inhibition in the neocortex. The visual manifestation of psychedelic-induced network instability is thought to be recursive visual hallucinations. Only the simplified fully-recurrent network produced output patterns characteristic of psychedelic-induced visual hallucinations. This is unsurprising given that motion vision is mediated by recurrent processing in humans and other animals. However, these

psychedelic patterns were only elicited when using the training set, not when using the testing set. Furthermore, they were not consistently produced from every example within the training set. Nevertheless, motion trail-like artifacts were produced by reducing inhibitory weights, remarkably similar to the visual hallucinations produced by the use of psychedelic drugs. This corroborates with and provides more evidence for the prevailing theory of psychedelic action—visual hallucinations from psychedelic drugs occur as a result of weakened lateral inhibition and errant recurrent excitation within the visual cortex.

The results of this study must be interpreted alongside its limitations. The same training and testing sets were used in all three experiments. While this provides consistency, particular qualities of these example sets may have significantly impacted network performance and output. There are several unknowns throughout these experiments, particularly in the error rate provided by LENS software. As mentioned, sometimes the error rates produced did not seem to correspond with the actual outputs and targets of the network. The algorithm for error rate is not listed in the software's documentation. Furthermore, despite attempts at biological realism, the network designs are essentially arbitrary, especially after the failure of the original biologically-constrained fully-recurrent network.

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