Evolutionary Generation of Visual Motion Illusions

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Abstract: Why do we sometimes perceive static images as if they were moving? Visual motion illusions enjoy a sustained popularity, yet there is no definitive answer to the question of why they work. We present a generative model, the Evolutionary Illusion GENerator (EIGen), that creates new visual motion illusions. The structure of EIGen supports the hypothesis that illusory motion might be the result of perceiving the brain’s own predictions rather than perceiving raw visual input from the eyes. The scientific motivation of this paper is to demonstrate that the perception of illusory motion could be a side effect of the predictive abilities of the brain. The philosophical motivation of this paper is to call attention to the untapped potential of “motivated failures”, ways for artificial systems to fail as biological systems fail, as a worthy outlet for Artificial Intelligence and Artificial Life research.

Keywords: Artificial Perception, Visual Illusions, Illusory Motion, Artificial Intelligence, Neural Network

1. INTRODUCTION

The human perceptual system falls into the category of “complex systems”, where many parameters influence each other in ways that are difficult to disentangle. Complex systems can fail in ways that are exceptionally rich in information, and studying these failures teaches us more about those systems than we would learn by only observing successes [1]. To help exploiting failure cases in the quest to understand complex systems, we have been advocating for an approach that focuses on replicating biological failures in artificial systems. The approach follows these steps: 1. Document a failure (e.g. sudden loss of performance) in the biological system of interest; 2. Replicate the transition from failure to success in an artificial system; 3. Document novel failures in the artificial system; 4. Verify that the artificial failures replicate in the original biological system. This approach increases the likelihood that the artificial and biological system share causal mechanisms, rather than only displaying shallow resemblances. Applied to the field of perception studies, and given that perception is by definition imperfect, we simply call this approach “Artificial Perception” [2].

Humans (and many other animals) do not have direct conscious access to raw data from the outside world. Input can be heavily processed by sensory cells even before it reaches our brain, and further processed by various brain networks before reaching our awareness. For example, touch neurons in human skin have been found to compute the edge of objects before sending that information to the brain [3]; in the visual system, the eye performs some complex computations of its own [4], after which the brain itself performs high speed, unconscious computations before the information reaches our perception. This processed information, as well as our expectations, act as feedback that further modify incoming perceptual information [5]. All of this intermediate data processing makes our perceptual system especially prone to errors of perception that are difficult to control or correct.

Illusions are some of the most spectacular, widespread, and enjoyable perceptual failures. Among the many existing definitions of “illusion”, this paper uses the following: an illusion is a perception that not only misrepresents reality, but can also be recognized by the observer through their other senses as a misrepresentation of reality. Furthermore, the knowledge that reality and perception do not match does not destroy the illusion [5]. In summary, an illusion is a faulty perception that persists despite conscious knowledge and experience of the corresponding reality. A number of Artificial Neural Network models have been found to respond to different types of visual illusions: color constancy illusions [6], closure effects [7], the flash-lag effect [8], the scintillating grid illusion [9], orientation illusions [10], length illusions [11]. At least one paper also tackles the task of synthesizing new illusions using neural networks, in this case to change the brightness or color perception of grey squares [12] on generated backgrounds. This paper focuses on a type of visual illusion called “illusory motion,” [13] where a single static image is perceived as if it were moving. In [13], 75% of participants reported perceiving illusory motion in the Fraser-Wilcox illusion, although the sensitivity to a given image seems to vary greatly. Fish, flies, monkeys, lions and cats have also been found to react to illusory motion [14-18], although it is unclear whether they perceive it as a “normal” motion or if they are aware that the motion is illusory.

Motion illusions, such as the famous Rotating Snakes Illusion [19], are typically created by trial and error. It is unclear why they work, and without a causal explanation it is difficult to devise a systematic and exhaustive method to generate motion illusions. So far, we know that they seem to be influenced by eye saccades [20], eccentricity and lighting [21], and often but not always require contrast changes. The con-
cept of Predictive Coding could provide much needed clues into the causal mechanisms of illusory motion. Predictive coding is the idea that our brains are always trying to predict the world around them. Watanabe et al. [22] showed that a predictive deep neural network architecture called Prednet [23], engineered based on predictive coding principles [24], was tricked by motion illusions but not by similar images where the illusion was broken. Prednet was trained using the First Person Interaction dataset (FPSI) [25], a first-person video of people going to an amusement park, filmed unrelated to any illusion research projects and a priori free of any purposefully introduced visual illusion. The task of the network was to predict future frames of the video. After training, the network predicted a rotating motion in the Rotating Snakes illusion, and no motion in a version of the illusion where the colors were swapped. Thus Step 1 and 2 of the Artificial Perception approach were cleared: 1. Documenting a failure (illusory perception of motion) in the biological system of interest, and 2. Replicating the transition from failure to success in an artificial system. Here we show that Step 3 (“Document novel failures in the artificial system”) can also be cleared, and present some evidence towards Step 4 (“Verify that these failures replicate in the original biological system”). If all 4 steps can be cleared, it will strongly suggest that as the main common point between the biological and artificial system, predictive coding is a major cause of illusory motion perception.

In Section 2 we describe the architecture of the illusion generator and its main parameters. In Section 3, we present some of the generated illusions and their common points with existing motion illusions. Finally in Section 4, we explain some of the strengths and weaknesses of the presented results.

2. METHODS

2.1. Open Source Materials

The architecture described here is named Evolutionary Illusion Generator (EIGen), pronounced as in “eigenvalue”. It is available at https://github.com/LanaSina/evolutionary_illusion_generator

The predictive models used as a plug-in evaluator is available at https://doi.org/10.6084/m9.figshare.13280120 (black and white) and https://figshare.com/articles/Sample_Weight_Model_Front_Psychol_15_March_2018_/11931222 (color).

A collection of generated illusions is available at https://figshare.com/articles/figure/EIGen_Visual_Illusions/16800013

2.2. Architecture

EIGen is composed of two main parts (Fig. 1): a generator and an evaluator. The evaluator is based on a fully pre-trained predictive neural network model and a visual flow calculator. The predictive model is in advance trained to predict video frames: taking a sequence of frames extracted from a video as input, the model has to output an image prediction as similar as possible as the next video frame [23]. We use two models: one trained on the original color video from the First Person Interaction Dataset [25] (now unavailable from the original source, but copied here https://figshare.com/articles/figureFPSI_frames/7819574/1) and one trained on a black and white (grayscale) version of the video. Note that the results can be replicated with different datasets, as long as the model is shown to detect motion on well-known motion illusions. In EIGen, a single image is repeated 20 times to make a (static) input sequence. The output of the predictive model reveals the model’s assumptions about whether the image is moving or not. As the input is just one static image, the correct prediction would be a perfect copy of the input image. Therefore, we take any predicted motion as analogous to the illusory motion that humans perceive in static images. To estimate the direction and velocity of the predicted motion, we use the Lucas–Kanade method of calculating the optical flow. This method compares two images and outputs the estimated origins and amplitudes of motion vectors originating from one image and leading to the other image.

The generator module of EIGen uses Compositional Pattern-Producing Networks (CPPNs) [26] to generate output images, and an evolutionary algorithm to optimise the CPPNs. The evolutionary algorithm used here is NeuroEvolution of Augmenting Topologies [27] (specifically its python implementation [28]). The algorithm generates and evolves several families of genomes, keeping the families as diverse as possible. It iteratively selects the best genome in each family according to a user-defined fitness function, and outputs the best genome of the best family. The genomes are evaluated as follows: first, the CPNN genome produces an image. The evaluator module returns the group of motion vectors associated to this image. The group of vectors is scored according to our fitness function. This score is used to rank the genomes against each other.

The reasoning behind our choice of fitness function is linked to the type of failure cases seen in Fig. 5, but in summary, the best group of motion vectors is one that has: (a) numerous vectors, indicating many sources of illusory motion; (b) vectors as big as possible, indicating a strong illusory motion, but not too big (huge motion vectors tend to be

**Fig. 1.** The structure of EIGen. A Predictive Neural Network (PNN) is trained in advance to predict video frames. It is then used in combination to optical flow calculation to rate the strength of illusory motion in images generated by Compositional Pattern-Producing networks (CPPN). The CPPNs are optimized by an evolutionary algorithm.
The smaller image at the bottom of each illusion represents the motion predicted by the network. The vectors origins are marked as yellow dots; the amplitude is multiplied by 60 for easy visualisation. We typically evaluate the visual flow on white background but the background color does not seem to influence the results.

due to instabilities in the optical flow module); (c) orientation and sense closely aligned to the some of the neighboring vectors, indicating agreement in the predicted motion; (d) opposite sense to the some of the neighboring vectors, indicating contrast in the predicted motion. For reasons that are not entirely clear, (d) seems to be necessary for humans to perceive the illusory motion, despite the fact that this condition does not objectively increase the amount or strength of motion vectors. Note that although not openly acknowledged, conditions (a) to (d) also accurately describe the vast majority of human-designed illusory motion images. In practice, to simplify the task of the network, we constrain the structure of the output images to circles with concentric bands of repeating patterns, the patterns on neighboring circles being inverted (Fig. 2). In itself (for example when filled with random colors) this structure is not sufficient to induce illusory motion, but makes it easier for the generator to fulfill conditions (c) and (d). It is similar to the structure often used in the Rotating Snakes illusion.

One generation of the genetic algorithm corresponds to one pass through each module: generating or mutating genomes and scoring the corresponding images. The next generation is created from the best genomes. EIGen can run indefinitely; we typically stop it when it converges (the best image remains the same from generation to generation) or when the fitness score seems high.

2.3. Parameters

PredNet parameters: image width = 160, image height = 120; input length = 20 images; extension duration = 2 images. NEAT parameters: species size = 10 individuals, population = 5 species.

3. RESULTS

We first present results obtained with the black and white model. Fig. 2 shows novel illusions, while Fig. 3 presents illusions that happen to reproduce known illusions. Common tips to best experience the illusory motion include using good lighting and slowly moving one’s gaze around the image rather than focusing on one point. While the authors
These images seem to produce in general less strong illusions in humans than the black and white model. One possible difference with human-generated color illusions is that humans seldom use color gradients.

have not yet formally gathered data from human experiments for the novel illusions, the fact that EIGen could rediscover existing illusions, and predict motion in the expected orientation, is a hopeful sign of the agreement between the artificial and the biological data. Informal polls reveal that while not everyone can see the illusory motion (the same can be said of human-designed illusions), those that do see the illusion perceive a motion of the same nature as predicted by the network: clockwise/counterclockwise rotations, or expansions/contractions. Note that while the orientations are the same, the sense of the predicted motion vector seems to be opposite from the human perceived motion. The authors have several hypotheses about this phenomenon but no airtight explanation. Nevertheless, the orientation and sense of the motion, both in the biological and artificial system, seems to depend on the direction of black/white luminosity gradients [31], or in the extreme case of the medaka illusion, purely on the smooth change in the relative amount of each color.

Fig 4 presents results obtained with the full color model. Given the vast space of possible patterns, it is difficult to relate these illusions to existing human-designed illusions. One constant is that the direction of motion follows the direction of the luminosity gradient. Anecdotally, we also observe that the color model often produces less convincing illusions than the greyscale model. The motion is less strong than common human-designed color illusions. One possible difference with human-designed color illusions is that humans seldom use color gradients.

Finally we present examples of failed illusions (Fig.5, where the model predicts a motion but no motion is perceived by the authors or other humans in an informal poll. These illusions were all obtained with fitness functions that did not follow the 4 conditions outlined in the Methods section.

4. DISCUSSION

This paper presents a model, EIGen, that generate new visual illusions by coupling artificial neural networks and genetic algorithms. EIGen represents Step 3 of the Artificial Perception approach for illusory motion: we document novel failures, in this case illusory motion, in an artificial system. Although the most crucial step, “Verify that the artificial failures replicate in the original biological system,” is still missing, we show that EIGen rediscovers existing illusions: this suggests that at least a subset of the generated illusions shares all characteristics of illusions that work on humans. Three heavy weaknesses remain: first, we have not yet gathered human data about the perception of the illusions generated by EIGen. Second, we heavily constrained the structure of the generated illusions to hasten convergence: it is unclear if the model would have converged without this help. And third, we have no justification for 3 of the 4 conditions that we implemented in the fitness function. It makes sense that bigger motion vectors makes for stronger illusions, but why is it better to have more vectors? Why do the vectors need both a level of agreement and a level of disagreement for the illusion to be perceived by humans, while the model predicts motion either way? Clearly, the model does not entirely overlap with human perception, as it produces motion vectors when these conditions are not satisfied. Nevertheless, it seems fair to say that this paper strengthens the idea that predictive coding is involved in the perception of illusory motion in humans.

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