Modeling the Hallucinating Brain: A Generative Adversarial Framework

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Abstract—This paper looks into the modeling of hallucination in the human’s brain. Hallucinations are known to be causally associated with some malfunctions within the interaction of different areas of the brain involved in perception. Focusing on visual hallucination and its underlying causes, we identify an adversarial mechanism between different parts of the brain which are responsible in the process of visual perception. We then show how the characterized adversarial interactions in the brain can be modeled by a generative adversarial network.

Index Terms—Generative Adversarial Network (GAN), Brain, Hallucination.

I. INTRODUCTION

BRAIN is an essential organ of the body for information processing and memory. Therefore, discovering the functionality of the brain has always been a challenge in neuroscience, which has drawn special attention in the past two decades. So far, various aspects of the brain’s functionality and structure have been identified. Moreover, the symptoms of different brain-related neurological disorders have been revealed, for many of which effective treatment/symptom control drugs have also become available nowadays.

The functionality of each particular area in the brain, and the connectivity between different areas are essential for reacting/responding to different stimulating input signals [1], [2]. Neurotransmitters serve as a means to connect the different areas of the brain, which allows them to interact together for information processing [1], [2]. Factors such as aging or neurological disorders can lead to certain brain damages. One of the known symptoms of many brain diseases is hallucination. Hallucinations can occur in a wide range of diseases such as in Schizophrenia, Parkinson’s disease, Alzheimer’s disease, migraines, brain tumors, and epilepsy.

Hallucinations are the unpredictable experience of perceptions without corresponding sources in the external world. There are five types of hallucinations: auditory, visual, tactile, olfactory, and taste. Visual hallucinations occur in numerous ophthalmologic, neurologic, medical, and psychiatric disorders [3]. Visual hallucinations are common in Parkinson’s disease, with a reported prevalence as high as 74% after 20 years of the disease [4]. Positive symptoms of schizophrenia are hallucinations, delusions, and racing thoughts. Focusing on hallucination, in this paper, we propose an artificial intelligence (AI) framework for modeling visual hallucinations (VHs).

Today, probabilistic mathematical and AI techniques have come to assist neuroscientists in analyzing the brain functionality. This includes deep learning (DL), reinforcement learning (RL), and generative adversarial networks (GANs) [5]. For instance, in [6] the neural mechanisms have been studied via probabilistic inference methods. The brain’s structural and functional systems are seen to possess features of complex networks [7]. It is also shown that neurons as agents, can understand their environment partially, make a decision, and control their internal organs [8]. Moreover, Yamins et al. use deep hierarchical neural networks to delve into computational sensory systems models, especially the sensory cortex and visual cortex [9].

Recently, utilizing the idea of Generative Adversarial Network (GAN), Gershman has proposed an adversarial framework for probabilistic computation in the brain [10]. There, he explains the psychological and neural evidence for this framework and how the generator and discriminator’s breakdown could lead to delusions observed in some mental disorders. GANs, which were introduced by Goodfellow in 2014 [5], are generative models which allow for the...
Figure 1. The overall framework of the generative adversarial network (GAN) architecture. The generator contains a generative network and a discriminative network. The generator generates a new image by random inputs. This generated image is sent to the discriminator alongside real images. The discriminator takes input images and classifies them into two classes: real and fake.

This paper looks into the evidence within the neurobiology and neuropsychiatry of the human brain aiming at developing a generative adversarial framework for approximate inference in the hallucinating brain. In Section 2, we briefly review the idea of GAN as a preliminary. In Section 3, we point out the relevant evidence within the mechanism of visual hallucinations. Then, we develop our framework for visual hallucinations in Section 4. Finally, we discuss the challenges of this framework in Section 5.

II. GAN IN BRIEF

Generative adversarial network (GAN) is a generative model in which a generator network (GN) and a discriminator network (DN) contest with each other, in an adversarial setting (in Fig 1). In this setting, the DN and the GN play the two-player minimax game. GANs can be used for both semi-supervised and unsupervised learning [13]. The common analogy for GAN is to think of GN as an art forger and DN as an art expert. The forger creates forgeries to make realistic images, and the expert receives both forgeries and real (authentic) images and aims to tell them apart. Both of them are trained simultaneously and in competition with each other, as shown in Fig. 1.

In words of statistical learning, on the discriminator side, DN has a training set consisting of samples drawn from the distribution $p_{data}$ and learns to represent an estimate of the distribution. As a result DN is to classify the given input as real
or fake. On the generator side, GN is learned to map noise variables $z$ onto samples as genuine as possible, according to the prior distribution of the noise variables $P_z(z)$. This way, GN and a DN contest in a two-player minimax game. In this game, DN intends to maximize the probability of distinguishing between the real samples and those generated by GN. As for GN, it aims to minimize the probability of detecting the fake samples by DN. The relevant objective function can be written as:

$$\min_G \max_D E_{x \sim P_{data}}(x) \log D(x) + E_{z \sim P_z(z)} \log(1 - D(G(z)))$$  \hspace{1cm} (1)$$

Indeed, by such ability in generating synthesized data, GANs will come to our aid in many applications such as super-resolution, image caption generation, data imputation, etc., in which lack of sufficient real data has been a challenge. In this paper, however, we benefit from GAN from a modeling perspective. In particular, we take advantage of GAN adversarial framework as a basis for modeling visual hallucinations. In the next section, we briefly review what hallucination refers to in view of brain’s neurology.

III. HALLUCINATION

In a healthy brain, when the human sees an object, some human brain areas interact together. It is as a result of such interactions between different areas of the brain that the human perceives the object. For example, Fig. 2 shows the functional anatomy of a healthy human brain with regards to vision. As it is shown on the figure, the information passes from the retina via the optic nerve and optic tract to the lateral geniculate nucleus (LGN) in the thalamus. The signals project from there, via the optic radiation to the primary visual cortex-cells which process simple local attributes such as the orientation of lines and edges. From the primary visual cortex, information is organized as two parallel hierarchical processing streams [4]:

1) The ventral stream which identifies the features of the objects and passes them from the primary visual cortex to the inferior temporal cortex.
2) The dorsal stream which processes spatial relations between objects and projects through the primary visual cortex to the superior temporal and parietal cortices.

Finally, the prefrontal cortex areas (such as the Inferior frontal gyrus and Medial Prefrontal Cortex) analyze the received data from other areas by real and fake point of views.

If the connectivity between any of the above explained brain areas is disrupted, humans cannot understand the object or may perceive it falsely. A relatively common form of memory distortion arises when individuals must discriminate items they
have seen from those they have imagined (reality monitoring) [14]. In some neuro-diseases, individuals cannot discriminate whether an item was imagined or perceived. In this regard, hallucinations are defined as the unpredictable experience of perceptions without corresponding sources in the external world [15].

Now, in order to model the interaction of different brain areas with regards to hallucinations, we look into the known or suggested causes for the incidence of hallucinations. In particular, some studies show that hyperdopaminergic activity in the hippocampus makes hallucinations in schizophrenia [16], [17]. Also, a grey matter volume reduction is seen in Parkinson’s disease patients with visual hallucinations involving Occipito-parietal areas associated with visual functions [18]. The hippocampal region dysfunction and abnormalities in GABA$^{1}$ and DA$^{2}$ function is seen to have a role in causing this disease [19]. Abnormal cortical dopamine D1/D2 activation ratio may be related to altered GABA and glutamate transmission [20].

In order to model hallucination, we consider the areas of the brain involved in hallucination, according to the previous relevant studies [4], [17]. Visual hallucinations in Parkinson’s disease are caused by overactivity of the Default Mode Network (DMN) and Ventral Attention Network (VAN) and underactivity of the Dorsal Attention Network (DAN) [4]. VAN mediates the switch between DAN and DMN. Overactivity of DMN and VAN reinforces false images, which DAN fails to check when it is underactive [4]. Moreover, on functional neuroimaging studies, patients with visual hallucinations showed decreased cerebral activation in occipital, parietal, and temporoparietal regions and increased frontal activation in the region of frontal eye fields [21].

It is important to note that brain connections are not static but rather dynamic as they change all the time. According to aforementioned areas involved in hallucinations, and the effect of neurotransmitters in the connectivity between different areas of the brain, one can conclude that imbalance between dopamine, acetylcholine, and other neurotransmitters is involved in the pathogenesis of visual hallucinations. Inspired by all the above, in Section IV we present a theoretical GAN-based generative model for hallucinations, which highlights the functional importance of brain areas, their connections, and neurotransmitters.

IV. Modeling Hallucination with GAN

This section presents a model for hallucination in the framework of generative models. Individuals use a number of different types of retrieved information (e.g., perceptual detail, information about cognitive operations) to determine whether an item was imagined or perceived. As explained in the previous section, a breakdown in the connectivity of neural networks and dysfunction of some brain areas is known to results in visual hallucinations. In this condition, some brain areas, especially the occipital lobe, the visual cortex, and the parietal area change their mechanisms. Specifically, they process imperfect visual input data and send output to other areas. This somehow mimics the role of GN in GAN, trying to change the visual input data in order to deceive the other areas which were responsible for the perception between reality and imagination (resembling DN in the GAN setup). In particular, some cortical areas, especially the prefrontal cortex and inferior frontal gyrus, process the input to determine whether an item was imagined or perceived. As mentioned in Section III the perturbations in some neurotransmitters, especially dopamine, impacts the functionality of these areas. As a result, these areas cannot truly classify the input to determine whether an item was imagined or perceived. This imperfect functionality thus initiates a contest between the distinguishing region and the falsifying region which function in adversarial setup. Putting the two aforementioned sides together, the adversarial interaction between the mentioned areas of the brain can be viewed as a GAN network. Table I summarizes the correspondence between the elements of the hallucinating brain and their counterparts within the relevant GAN model.

Consequently, the hallucinating human brain’s vision system looks like GANs [5]. The generative adversarial perspective, unlike Bayesian models, suggests a broad hypothesis about the origin of hallucinations content (via an abnormal generator)like delusion. GN formalizes the occipital lobe, visual cortex, and parietal area functionality in the

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$^{1}$γ-Aminobutyric Acid

$^{2}$Dopamine
Table I

| Attribute                  | Models                                      |
|----------------------------|---------------------------------------------|
| **GAN**                    | **Brain with Hallucination**                |
| Generator                  | Neural network                             |
| Discriminator              | Neural network                             |
| Input of Discriminator     | Images                                      |
| Output of Discriminator    | Fake or Real                                |
| Input of Generator         | Noise                                       |
| Output of Generator        | Fake Image                                  |
| Neuron                     | Artificial Neuron                           |

hallucinating brain. Also, the discriminator directly formalizes the prefrontal cortex and Inferior frontal gyrus functionality and ideas about reality monitoring that have been applied to hallucinations [10].

V. DISCUSSION

In this paper we explored the neurobiology of hallucinations from a modeling perspective. In this regard, we developed a generative adversarial framework for modeling visual hallucinations. Specifically, we demonstrated the mappings between the areas of a hallucinating brain and the elements within GANs. On the neurological side, dopamine is critical for reinforcing actions consistent with behavioral learning theories, while several other neuromodulators are implicated in creating new memories. Therefore, neurotransmitters are vital for the brain areas to react concertedly. Any perturbation in the functioning of the neurotransmitters, such as that in visual hallucinations, changes the mechanisms of different brain areas. This leads to an adversarial mechanism among the responsible brain areas. Focusing on this phenomena, the present study raises the intriguing possibility that the areas of a hallucinating brain interact with each other through an adversarial mechanism which can be modeled by GAN.

This is of course a first step, and questions on the role of imagination in this setup remain to be further explored. Specifically, questions such as how imagination can become involved in learning (imagination-based learning) and also in the modeled adversarial interactions, is yet to be answered in future research. Adversarially learned inference [22] can be used as one particular approach to such future studies. In particular, adversarially learned inference uses imagination to drive learning, exemplifying a broader class of imagination-based learning models that have been studied in cognitive science [10].

Another broad issue concerns how to evaluate the performance of the model and check the functional and structural constraints. Therefore, another interesting direction for future work is to seek for a suitable evaluation method, which would allow for model validation as an important step. Finally, the possibility of generalizing the proposed adversarial framework to other types of hallucination would also be of interest.

VI. CONCLUSION

In the context of modeling functions of the human brain, we presented a model for the hallucinating brain. Focusing on visual hallucinations and some of its sofar known neurological causes, we characterized an adversarial mechanism between different areas of the brain. We then showed how this adversarial setup can be modeled by GAN. The proposed model can be viewed as the first steps of an addendum to the results of [10], providing evidence on how the idea of generative adversarial brain can be extended to hallucinations as well.

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