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Hierarchical Causality Network: Find the Effective Connectivity in Visual Cortex^{*}

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Abstract. Studying the human brain is of great significance to the development of AI. The analysis of fMRI brain signal of visual cortex is a research hotspot in this field. One of key issues in analyzing fMRI brain signals is how to establish effective connectivity model from brain signals. Traditional analysis methods regard voxel correlations as effective connectivity. However, the result obtained by these methods are not effective connectivity but functional connectivity. To achieve real effective connectivity, we need to analyze the causality relationship between voxels. Therefore, we propose a hierarchical causality network model (Hcausal-Net). The model stratifies the voxels of the visual cortex in fMRI brain signals, and analyzes the causality relationship between voxels by Granger Causality Analysis (GCA), and then infer the effective connectivity given by Hcausal-Net. The voxels sensitive to the stimuli are extracted, and the forward encoding process model of visual perception is established. Finally, in the experiment, we also improved the image restoration method based on machine learning and conduct comparative experiments, and the results are better than the previous work, which proves the effectiveness of the model proposed in this paper.

Keywords: Brain-inspired computing, visual perception, fMRI, Hierarchical Causality Network (Hcausal-Net), Granger Causality Analysis.

1 Introduction

The neural mechanism of the human brain completing the visual information processing is a very valuable research topic [1]. It is of great significance for the development of a new model of AI and algorithm of intelligent computing such as image

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recognition, scene understanding, semantic understanding [2]. Blood Oxygen Level-Dependent functional Magnetic Resonance Imaging (BOLD-fMRI) is an emerging brain signal acquisition technology that can display high-level brain activity in the form of images [3]. The analysis of fMRI brain signals of visual cortex is a research hotspot in this field [4].

In the past decade, a series of studies have been carried out on fMRI brain signals of visual cortex by using various methods. Initially, researchers used statistical methods and Bayesian inference to establish the model of fMRI brain signals [5, 6]. In recent years, Deep Neural Networks (DNNs) [7], Deep Canonically Correlated Auto-Encoders (DCCA) [8], Variational Auto-Encoder (VAEs) [9], Semantic Attractor Networks [10] and other methods [11, 12] have been used to research this question. Nowadays, analyzing fMRI brain signal of visual cortex has become a hot research field and still has a broad space for development.

In the research of fMRI brain signals, the connectivity between voxels is the focus [13], and the connectivity between voxels can be divided into three categories: structural connectivity is biological connection [14], and functional connectivity is the correlation of responses [15], and effective connectivity is the causality of responses [16]. However, most existing connectivity models ignored the effective connectivity information, which may provide information about the information flow in the brain.

In 2019, the author's team proposed Hierarchical Correlation Network (Hcorr-Net), which focus on the correlation relationship in visual cortex, and analyzed the fMRI brain signals of visual cortex and established a hierarchical model of the visual cortex [17]. However, there is a flaw in this model: it doesn't use causality analysis method, which may confuse the effective connectivity with the functional connectivity. To solve this problem, in this paper, we proposed Hierarchical Causality Network (Hcausal-Net), which is a hierarchical causality model based on previous work. The Hcausal-Net model replaces the correlation analysis with Granger Causality Analysis (GCA), so that the result is true effective connectivity rather than functional connectivity. Then, based on the Hcausal-Net, we establish the forward encoding process of visual information and apply it to the image reconstruction model to verify the effectiveness.

The contents of this chapter are arranged as follows. Section 2 introduced the previously proposed Hcorr-Net model. Section 3 proposes the framework of the hierarchical causality model Hcausal-Net. Section 4 describes the process of forward encoding, including data classification and image reconstruction. In section 5, we design experiments and collect fMRI brain signal data, and use those data to verify the performance of the method proposed in this paper. In section 6, conclusions are given.

2 Hierarchical Correlation Network

In 2019, the author's team proposed Hierarchical Correlation Network (Hcorr-Net), which is a hierarchical correlation model for analyzing the brain connectivity in visual perception process [17]. Hcorr-Net models the forward encoding process of visual information in the human brain by analyzing the correlation between voxels in fMRI data,

and applies it to the encoding and decoding of visual information, and reconstruct the visual stimulus picture from fMRI brain data.

The Hcorr-Net model treats each brain area in the visual cortex as a layer in the network, and treats each voxel in the brain area as a node in a layer of the network, and established a hierarchical forward coding model from image to low-level visual cortex and then to high-level visual cortex. The correlation between voxels and the correlation between voxel and pixel is determined by calculate the Pearson correlation coefficient. Through the above methods, the receptive fields of pixels in the brain were finally determined, revealing the effective connectivity in visual cognitive tasks.

But with further research, we believe that the previous work could be improved. First, in Hcorr-Net, when we analyze the correlation between voxels, only the Pearson correlation coefficient is calculated. This method is too simple and can be improved. Second, in Hcorr-Net we only analyzed the correlation between voxels, and thought that is causality relationship and that is effective connectivity. However, correlation is not the same as causality [18]. Even if there is a correlation between two voxels, there may not be a causality relationship between two voxels. The causality relationship has not been fully considered in Hcorr-Net model, so it can be improved.

3 Hierarchical Causality Network

In order to solve the problems of Hcorr-Net, we use the method of Granger Causality Analysis (GCA) to rebuild the forward encoding model and propose the Hierarchical Causality Network (Hcausal-Net). The framework of our method is shown in Fig. 1.

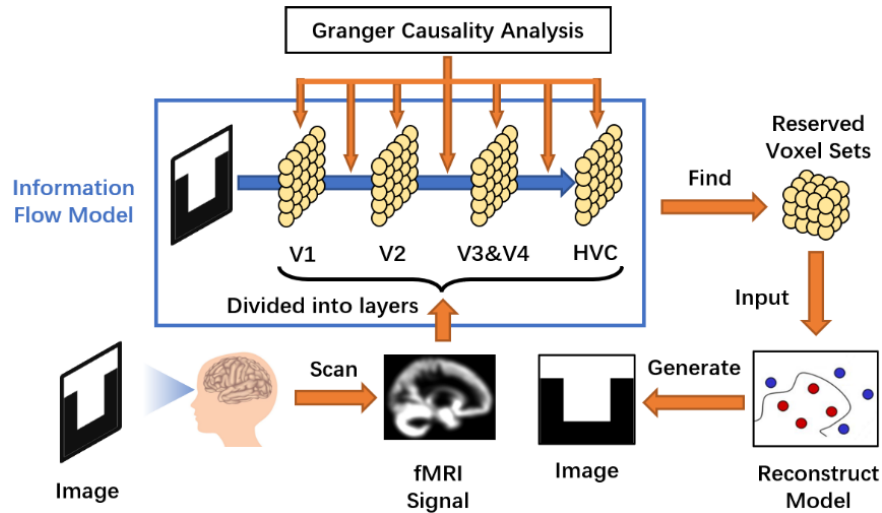


Fig. 1. The framework of our method.

3.1 Granger Causality Analysis

Granger Causality Analysis (GCA) is a method for analyzing the causality between time series [19]. It is based on Vector Autoregressive model (VAR), and by it we can find the causality relationship between two time series without prior knowledges. Nowadays, GCA has become a common method for fMRI brain signal analysis [20].

Suppose there are two time series $X = \{x_1, x_2, \dots, x_n\}$ and $Y = \{y_1, y_2, \dots, y_n\}$, and n is the number of time points. Now we want to judge that if Y is a cause of X by GCA. First, we build the Vector Autoregressive equations, predicting the value of X by the history information of X :

$$x_j = \sum_{i=1}^k a_i x_{j-i} + \sigma_j, \quad j = k+1, k+2, \dots, n \quad (1)$$

k is the degree of the model. $a_i (i = 1, 2, \dots, k)$ are parameters we need to estimate. $\sigma_j (j = k+1, k+2, \dots, n)$ are residuals. By solving those equations, we can get all those residuals, then calculate residual sum of squares (RSS) Ω_1 :

$$\Omega_1 = \sum_{i=k+1}^n \sigma_i^2 \quad (2)$$

Then, Add the information of Y to those equations to predict the value of X :

$$x_j = \sum_{i=1}^k b_i x_{j-i} + c_i y_{j-i} + \delta_j, \quad j = k+1, k+2, \dots, n \quad (3)$$

$b_i (i = 1, 2, \dots, k)$ and $c_i (i = 1, 2, \dots, k)$ are parameters we need to estimate. $\delta_j (j = k+1, k+2, \dots, n)$ are residuals. Then calculate the RSS Ω_2 :

$$\Omega_2 = \sum_{i=k+1}^n \delta_i^2 \quad (4)$$

The smaller RSS is, the better the quality of predictive equations is. If there is a causality relationship between Y and X , then the information contained in Y should be able to help the prediction of X , so Ω_2 should be smaller than Ω_1 . Therefore, GCA uses $F_{Y \rightarrow X}$ to measure the causality relationship between X and Y :

$$F_{Y \rightarrow X} = \ln \left(\frac{\Omega_1}{\Omega_2} \right) \quad (5)$$

The bigger $F_{Y \rightarrow X}$ is, the stronger the causality relationship between X and Y is. If there is no causality relationship between X and Y , $n \cdot F_{Y \rightarrow X}$ will obey $\chi^2(k)$ distribution. So, we can use hypothesis testing to judge whether there is a causality relationship between X and Y . If

$$F_{\chi^2(k)}(n \cdot F_{Y \rightarrow X}) \geq 1 - \alpha \quad (6)$$

there is a causality relationship between X and Y . Otherwise, there is no causality relationship between X and Y . $F_{\chi^2(k)}$ is the distribution function of $\chi^2(k)$ distribution. α is significance level.

3.2 Conditional Granger Causality Analysis

GCA can be used to analyze the causality relationship between two time series, but there are many voxels in fMRI brain signals and they can influence each other. There is a complex causality network in fMRI brain signal.

So, it may lead to a problem to use GCA directly. The problem is confusing causality with correlation. If voxel A can affect voxel B, and voxel A can also affect voxel C, then both the time series of voxel B and the time series of voxel C may contain part of the information of the time series of voxel A. Even if there is no causality relationship between voxel B and C, it may be misjudged that there is a causality relationship between voxel B and C because the information of voxel A is included.

Therefore, the result of GCA may be “fake causality”. To solve this problem, John Geweke proposed Conditional Granger Causality Analysis (CGCA) [21].

Suppose there are three time series X , Y , and Z . By GCA, it is judged that there is a causality relationship between Y and X . Now we need to judge whether there is a true causality relationship between Y and X , or that is just a correlation because of Z .

First, add the information of Z to the prediction of X :

$$x_j = \sum_{i=1}^k a_i x_{j-i} + b_i z_{j-i} + \sigma_j, \quad j = k+1, k+2, \dots, n \quad (7)$$

Then get the RSS Ω_1 . Then add both the information of Z and Y to the prediction of X :

$$x_j = \sum_{i=1}^k c_i x_{j-i} + d_i x_{j-i} + e_i z_{j-i} + \delta_j, \quad j = k+1, k+2, \dots, n \quad (8)$$

Then get the RSS Ω_2 . If there is a causality relationship between Y and X , Y should provide some information that is not contained in Z , which can make the prediction more accurate, so Ω_2 should be smaller than Ω_1 . Therefore, CGCA uses $F_{Y \rightarrow X|Z}$ to measure the causality relationship between X and Y that is independent of Z :

$$F_{Y \rightarrow X|Z} = \ln \left(\frac{\Omega_1}{\Omega_2} \right) \quad (9)$$

The latter process is the same as GCA.

CGCA provides us with a method to remove the interference of external factors to judge whether there is a causality relationship between two time series. When we establish the model of the causality relationship between many factors, we can use GCA to find causality relationship and use CGCA to remove “fake causality”, and finally we can find all the causality relationships between all the factors.

3.3 Hierarchical Causality Network

In this paper, we reconstruct the Hcorr-Net model by CGCA method, and the Hierarchical Causality Network (Hcausal-Net) is proposed to establish the model of the effective connectivity between voxels in the visual cortex and solve problems of Hcorr-Net. The framework of Hcausal-Net is shown in the Fig. 2.

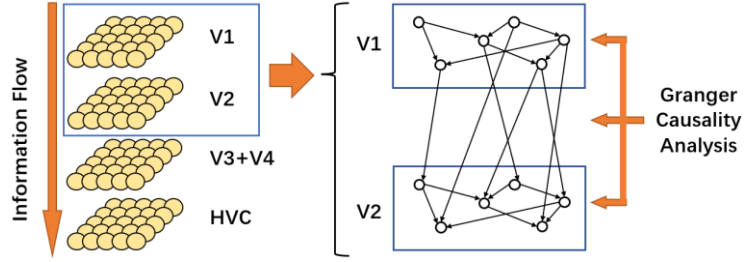


Fig. 2. The framework of Hcausal-Net.

In the Hcausal-Net model, we divide the visual cortex into 4 levels: V1, V2, V3+V4, and higher visual cortex (HVC), and analyze the voxel causality relationship within a layer (intra-layer causality) and the voxel causality relationship between layers (inter-layer causality). The causality relationship within a layer is the effective connectivity between the voxels in the same layer, and the causality relationship between layers is the effective connectivity between the voxels of two adjacent layers.

The effective connectivity network is established by GCA and CGCA. The essence of effective connectivity is the causality relationship between voxels. Two voxels with a causality relationship must have a correlation relationship. It means correlation is a necessary condition for causality, and causality is a sufficient condition for correlation. Correlation analysis is simpler than causality analysis. Therefore, we can use correlation analysis to help causality analysis.

Firstly, we analyze the correlation of all voxels by calculating the Pearson correlation coefficient and comparing it with a threshold. After the correlation analysis is completed, we use GCA to analyze the causality relationship. Since correlation is a necessary condition for causality, two voxels that don't have a correlation relationship must not have a causality relationship. Therefore, in the analysis, only the voxel pairs with correlation are analyzed, which greatly reduces the computational complexity.

After that, we use CGCA to remove all those "fake causality relationships", and find those true causality relationships in visual cortex. The algorithm of analyzing causality within a layer is shown in the algorithm. 1, and the algorithm of analyzing causality between layers is shown in the algorithm. 2. Algorithm 1 and algorithm 2 are both combination of hierarchical network proposed by authors team and GCA method.

First, find the effective connectivity within a layer. Then, for each pair of adjacent layers, find the effective connectivity between the two layers. Finally, we combine the two results together and get the effective connectivity network of visual cortex. That is the process of Hcausal-Net.

Algorithm 1 Analyzing Causality Within a Layer

Require:

There is a layer of Hcausal-Net L . $V = \{V_1, V_2, \dots, V_n\}$ is the voxel sets of L , and n is all voxel number of V . Each voxel is a time series, $V_i = \{V_{i1}, V_{i2}, \dots, V_{im}\}$, and m is the length. Granger Causality Analysis function $GCA(X, Y)$. Conditional Granger Causality Analysis function $CGCA(X, Y, Z)$. Threshold of correlation coefficient R .

Ensure:

Matrix $(C^L)_{n \times n}$. If V_j is a cause of V_i , $C_{ij}^L = 1$, otherwise $C_{ij}^L = 0$.

```

1:  $C^L = 0_{n \times n}$ 
2: for  $i = 1$  to  $n$  do
3:   for  $j = 1$  to  $i - 1$  do
4:     if  $\frac{Cov(V_i, V_j)}{\sqrt{Var(V_i) \cdot Var(V_j)}} > R$  then
5:        $C_{ij}^L = GCA(V_i, V_j)$ ,  $C_{ji}^L = GCA(V_j, V_i)$ ;
6:     end if
7:   end for
8: end for
9: for  $i = 1$  to  $n$  do
10:  for  $j = 1$  to  $n$  do
11:    if  $C_{ij}^L = 1$  then
12:      for  $k = 1$  to  $n$  and  $k \neq i, j$  do
13:        if  $C_{ik}^L = 1$  and  $CGCA(V_i, V_j, V_k) = 0$  then
14:           $C_{ik}^L = 0$ ;
15:        break;
16:      end if
17:    end for
18:  end if
19: end for
20: end for

```

Algorithm 2 Analyzing Causality Between Layers

Require:

There are two layers of Hcausal-Net, L_1 and L_2 . $V^1 = \{V_1^1, V_2^1, \dots, V_{n_1}^1\}$ and $V^2 = \{V_1^2, V_2^2, \dots, V_{n_2}^2\}$ are the voxel sets of L_1 and L_2 , and n_1 and n_2 are all voxel number of V_1 and V_2 . Each voxel is a time series, $V_i = \{V_{i1}, V_{i2}, \dots, V_{im}\}$, and m is the length. Granger Causality Analysis function $GCA(X, Y)$. Conditional Granger Causality Analysis function $CGCA(X, Y, Z)$. Threshold of correlation coefficient R .

Ensure:

Matrix $(C^{L_1 L_2})_{n_2 \times n_1}$. If V_j^1 is a cause of V_i^2 , $C_{ij}^{L_1 L_2} = 1$, otherwise $C_{ij}^{L_1 L_2} = 0$.

```

1:  $C_{i,j}^{L_1 L_2} = 0_{n_2 \times n_1}$ 
2: for  $i = 1$  to  $n_2$  do
3:   for  $j = 1$  to  $n_1$  do
4:     if  $\frac{Cov(V_i^2, V_j^1)}{\sqrt{Var(V_i^2) \cdot Var(V_j^1)}} > R$  then
5:        $C_{i,j}^{L_1 L_2} = GCA(V_i^2, V_j^1)$ 

```

```

6:   end if
7:   end for
8:   end for
9:   for  $i = 1$  to  $n_2$  do
10:  for  $j = 1$  to  $n_1$  do
11:  if  $C_{i,j}^{L_1L_2} = 1$  then
12:  for  $k = 1$  to  $n_1$  and  $k \neq j$  do
13:  if  $C_{i,k}^{L_1L_2} = 1$  and  $CGCA(V_i^2, V_j^1, V_k^1) = 0$  then
14:   $C_{i,k}^{L_1L_2} = 0$ ;
15:  break;
16:  end if
17:  end for
18:  end if
19:  end for
20: end for

```

4 Forward Encoding Process

The effective connectivity model proposed in this paper models the effective connectivity between voxels in the visual cortex, and by it we can clarify the transmission process of visual information in the visual cortex. According to the transmission process of the known visual information, the visual stimulation image can be inferred and reconstructed according to the fMRI brain signal.

The way of image reconstruction in this paper is the same as that of Hcorr-Net, the difference is using Hcausal-Net instead of Hcorr-Net. In Hcorr-Net, first, the image is decomposed into pixels, and the image reconstruction is realized by restoring the pixels one by one, and the problem is transformed into a single-output fitting problem. Adding visual stimulus image information Before the V1 layer, for each pixel, calculate the correlation coefficient between it and each voxel in V1 layer, then set the threshold and select all voxel sets in V1 layer that have correlation with image pixels; then, through the forward propagation model, find all the voxels that are related to the current pixel, and filter out the voxels that are not related to the current pixel by this method, and only keep the voxels related to the current pixel. Get all the voxels related to the current pixel, and then use them as input, and use the machine learning method to train the model to reconstruct the current pixel. Do this for each pixel and merge all those results, we can reconstruct the stimuli image.

In the work of Hcausal-Net, we maintain the advantage of Hcorr-Net that is able to cooperate with various machine learning methods. This paper will combine Hcausal-Net with Support Vector Machine (SVM) for image restoration to verify the effectiveness of Hcausal-Net, and compare the results with that of Hcorr-Net.

5 Experiments and Results

In this paper, a task-state fMRI experiment was designed and completed by us. Visual stimulus images are 8 geometric figures based on a 4×4 grid. All visual stimulus images are shown in Fig. 3.

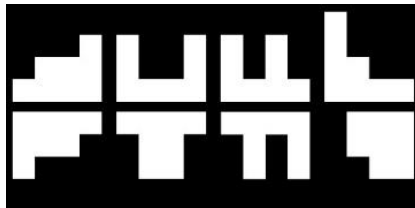


Fig. 3. Visual stimulus images.

At the beginning of the experiment, a preparatory phase was performed first, with a blank screen lasting 24s. After the preparatory phase is over, the subject of the experiment begins. In 18s cycles, a 9s blank was presented and followed by a 9s visual stimulus image before the next cycle was started. The subjects' fMRI brain signals were continuously collected throughout the experiment. Each image is presented 4 times in random order.

The experiment was completed in the First Affiliated Hospital of Xi'an Jiaotong University by using a 3.0-Tesla GE MR scanner. Five subjects aged between 20 and 25 were recruited in the experiment. Three male and two female read and signed the information sheet of magnetic resonance examination before the experiment. All subjects have normal vision or corrected vision, no history of mental illness or neurological disease, no psychological disease, no long-term medication, right-handed.

Before the start of the experiment, the subjects were shown and told the content of the experiment. Before the start of the experiment, the subjects were told to lie on their backs, breathe calmly, keep their heads still, stay awake, and focus on the central fixation point during the experiment.

The data collection process is as follows: First, collect T1 structural image data with the following parameters. Repetition Time (TR): 2250ms; Echo Time (TE): 3.06ms; Flip Angle: 90° ; Field of View (FOV): $214\text{mm} \times 214\text{mm}$; Voxel Size: $1\text{mm} \times 1\text{mm} \times 1\text{mm}$. After the acquisition of T1 structural image data, the experiment was carried out in turn to collect T2 functional image data. The parameters are as follows. Repetition Time (TR): 3000ms; Echo Time (TE): 30ms; Flip angle: 90° ; Field of View (FOV): $214\text{mm} \times 214\text{mm}$; Voxel Size: $3\text{mm} \times 3\text{mm} \times 3\text{mm}$. The screen resolution of the screen to display stimulative image is 800×800 and the refresh rate is 24Hz.

Finally, we obtained 5 sets of fMRI data for 5 subjects, each set of data is a four-dimensional matrix with a size of $61 \times 73 \times 61 \times 200$, of which the first three dimensions are the size of the 3D whole-brain fMRI image, and 200 is the time points number.

The data preprocessing of this experiment was done by DPABI software. During the preprocessing, we found that there are two sets of data that the quality of them is too

low, so we desert those data. Therefore, finally we got 3 sets of valid fMRI data. We only use the data of visual cortex.

Following the methods described in Chapters 3 and 4, Hcausal-Net is constructed to build an encoding model and we can use it for image reconstruction. The data of each subject were analyzed separately and were not pooled. After the above steps, the results of the reserved voxel set as shown in the Table 1.

Table 1. Reserved voxel num of all layers.

Subject	Layer	Reserved Voxel Num	All Voxel Num	Reserved Rate
Sub1	V1	470	1146	41.01%
	V2	517	2823	18.35%
	V3&V4	251	3093	8.12%
	HVC	21	3021	0.70%
	All	1259	10083	12.49%
Sub2	V1	394	1146	34.38%
	V2	156	2823	5.53%
	V3&V4	48	3093	1.55%
	HVC	17	3021	0.56%
	All	615	10083	6.09%
Sub3	V1	446	1146	38.92%
	V2	201	2823	7.12%
	V3&V4	78	3093	2.52%
	HVC	25	3021	0.83%
	All	750	10083	7.43%

Then use the model to do the image reconstruction, and compare the result with the result of Hcorr-Net. The correct rate of pixel is shown in the Table 2.

Table 2. Results of image reconstruction.

Subject	Hcorr-Net	Hcausal-Net
Sub1	65.63%	68.75%
Sub2	67.19%	74.11%
Sub3	60.94%	73.21%

The correct rate of the two-class model should be higher than 50%. Therefore, we drew a histogram with 50% as the baseline, as shown in the Fig. 4.

It can be seen from the table and the figure that the accuracy of image reconstruction is improved when the Hcausal-Net model is used compared to the model using Hcorr-Net, which verifies the effectiveness of the Hcausal-Net model proposed in this paper.

The higher the accuracy of image reconstruction is, the better the quality of information flow model is. Therefore, we can say that the Hcausal-Net model is better than Hcorr-Net model in the task of establishing model of the information flow in visual cortex.

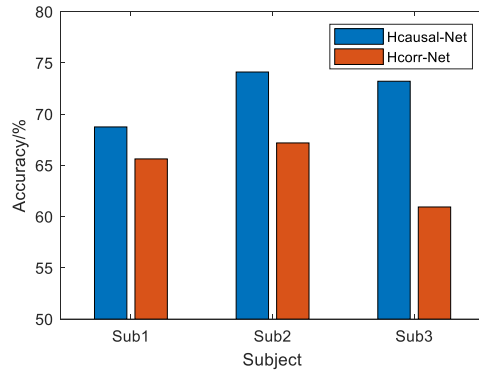


Fig. 4. Results of image reconstruction.

6 Conclusion

In this paper, we proposed Hierarchical Causality Network (Hcausal-Net) to explore effective connectivity in visual perception by establishing the model of the causality relationships between voxels of fMRI signals in the visual cortex. First, we introduced the Hierarchical Correlation Network (Hcorr-Net) proposed by the author's team, analyzed its defects and deficiencies. Next, we used Granger Causality Analysis method (GCA) instead of correlation analysis, and proposed the Hcausal-Net model to solve three problems: finding voxel causality network in visual stimulation tasks, using voxel causality network for encoding modeling. Then, we used fMRI data to restore visual reconstruction, and the results of image reconstruction show that Hcausal-Net has screened out effective fMRI signals and constructed a forward coding model for visual tasks. Finally, we compared the results of image reconstruction of the two models, and it is found that the Hcausal-Net model is better than the Hcorr-Net model in the image restoration task, which proves that the Hcausal-Net solves the inherent defects of the Hcorr-Net to a certain extent. The work of this paper helps to explain the neural mechanism of visual processing and contributes to visual scene understanding in the research of brain-like artificial intelligence. In the future, we will further verify the validity of the proposed model with more data. Furthermore, the eye-tracking data will be added to improve the robustness of the model.

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