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Research Article

Cognitive Neural Computation Modeling of Human Brain Information Storage and Extraction Based on Intelligent Computing

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With the development of neurological and brain science, human beings have more understanding of the memory mechanism of the brain. Therefore, using the memory mechanism of the brain to store and retrieve images is one of the most popular research fields in the world. Memory is an important part of the human cognitive system, and it is the basis for the realization of higher-level cognitive activities. Human perception and memory are closely related. If people lose the ability to perceive, then people's memory function will not be able to display. The current storage and extraction of brain information are mostly based on mathematical principles, without considering the memory mechanism in the brain, so the correctness and effectiveness of these methods are not high. Therefore, this study adopts an intelligent algorithm based on PCNN to denoise, segment, identify, and retrieve images. On this basis, a new learning method is adopted. This method can realize online incremental learning and can realize the storage of brain image data without predetermining the size and structure of the network. And when necessary, the information is extracted or not based on the distance between the detected versus the stored data. The test shows that when the number of images is 25, the present technique has an accuracy of 100% and the time required is 2345 s. Compared with the median filtering method, the efficiency of the present technique is greater.

1. Introduction

With the continuous development of cognitive neuroscience, human beings have more understanding of the memory mechanism of the brain. Therefore, using the memory mechanism of the brain to store and retrieve information is one of the most popular topics in the world. A large number of experiments have shown that it is a very effective method to use the memory mechanism of the brain to store and extract image information. According to the current research results, the memory of the human brain is a process of repeated evolution in the human brain through the process of memory, retention, and reproduction. Therefore, it is of great theoretical and practical significance to study the mechanism of human memory and apply it to computer vision, especially how to express, store, and retrieve when necessary in the brain.

Scientists have done the following research on cognitive neurocomputational modeling. Coccoli et al. believe that, in innovation, cognitive computing systems and big data are the key points [1]. How to use big data to improve human cognition is an important topic in the current field of intelligent computing. Chen et al. made a comparison and analysis from the aspects of deep learning data representation, cognitive model, parallel computing, and its application in big data environment. Several issues and development directions based on deep learning in big data are discussed, which provides a reference for future research [2]. The main problem of these studies is the low efficiency and accuracy of the model, for which this study introduces intelligent computing.

For intelligent computing, the main research results are as follows. Zhang et al. introduced various applications and technologies of integrated intelligent systems, as well as the advantages and disadvantages related to learning theory and expert systems [3]. With the rapid development of human society, the process of urbanization of the world population is also advancing rapidly. Urbanization brings many challenges and problems to urban development. Today, many countries are actively responding to the call for smart cities. Tong et al. discussed the current status of smart city development, provided the context of smart city development, and briefly defined the concept of smart city. Based on these definitions, a framework for the smart city is described. Various types of intelligent computing to make cities smarter are discussed and analyzed, along with specific examples [4]. Khan et al. proposed an intelligent computational method to study the resonance behavior of the Dauphin formula. The proposed method is a combination of artificial neural network and Firefly algorithm. A novel feature of ANN activation is the use of cosine functions and some error measurements are given in tables and graphs to discuss the convergence and accuracy of the scheme. The trajectories of the dynamical systems are also complemented with geometrical descriptions of the amplitude and angular frequency for different values of the phase level [5]. Saleem Durai and Sundaresan proposed a new intelligent computing framework that uses fuzzy machine clustering with extreme learning and formulates adaptive and cognitive energy and power allocation rules based on kernels [6]. Sabir et al. proposed a new standard for computational neural networks, using statistical operators to test the performance of GNN-PSO-SQPS to ensure the accuracy of research data [7]. In this study, intelligent data processing is introduced to improve the performance and accuracy of the model.

In the recall test trial, what the model does is extract semantic information about the test stimulus image. When the number of learning image samples is 5, the accuracy of the algorithm in this study is 63.2%, and the required time is 457 s; the accuracy of the median filtering algorithm is 42.1%, and the required time is 2192 s; when the number of learning image samples is 10, the accuracy of the algorithm in this paper is 65.6%, and the required time is 1076 s; the accuracy of the median filtering algorithm is 46.8%, and the required time is 4197 s.

2. Cognitive Neural Computational Modeling Methods

Generally, computational models based on cognitive psychology are only applicable to descriptive memory, that is, episodic memory and semantic memory. Contextual memory experiments generally include two stages: the learning stage and the testing stage [8]. A series of stimuli, such as a list of words, was presented to the subject to memorize. In the test, subjects reconfirmed (distinguishes what has been learned and what was not learned) or memory (from which detailed information learned is extracted), and recall is divided into cued recall, free recall, and associative recall [9].

Abstract models of episodic memory attempt to describe mental operations that enable reaffirmation and recall, but they do not specify how they are performed in the brain. Although there are huge differences between different scene memory retrieval modes, most of the current abstract modes share the same property: individual memory, which is the so-called "memory imprint" [10]. Storage is an individual's storage of transformed information in the brain for later retrieval when needed. Extraction refers to taking the information stored in the brain out and making use of it when the individual needs it. During learning, imprints are placed separately in long-term memory due to this independent assumption that new imprints will not have an impact on the integrity of previously stored imprints. The words in the study list will be saved as a scene image, where the scene vector is an incomplete and error-prone copy. Every time a word is learned, a new piece of information is stored into each feature. During the test phase, the model will be compared against all entries stored in memory based on the test hints. Adding this information all together, one can calculate an overall matching familiar signal [11]. Most hypothesized recognition memory is related to the overall degree of matching of the signal. Semantic memory is our ability to construct internal representations that allow us to predict what people cannot see [12].

The CLS model incorporated some widely accepted views on the division of labor between the hippocampus and the medial temporal cortex, explaining why the brain requires two distinct specialized learning and memory systems [2]. The CLS model is a biologically based model. The medial temporal cortex forms the bottom layer of the model's structure and is a distributed, overlapping system capable of incrementally integrating context to extract underlying semantic structures; the hippocampus is a sparse, pattern-separating system responsible for the rapid learning of episodic memory. Therefore, the medial temporal cortex is mainly responsible for semantic memory and the hippocampus is mainly responsible for episodic memory [13].

Memory elements in hippocampal and medial cortical networks are represented by excitatory activation patterns distributed across different network units. Excitatory activation propagates through positive synaptic weights, the overall level of which is controlled by other factors [14]. In the CLS model, learning takes place in the hippocampus and in subregions of the medial temporal cortex using simple learning rules. When the connection between transmitter and receptor neurons is strengthened, the connection between the two also weakens [15].

This model suggests that incremental learning occurs in the medial cortex, with each training resulting in relatively small adaptive changes in synaptic weights [16]. The model hypothesizes that this property enables the hippocampus to rapidly recall any event-related activity pattern, regardless of whether they are similar [17].

The hippocampal model applies the generally accepted ideas about how the hippocampus works [18]. In the brain, the entorhinal cortex forms a bridge between the hippocampus and the cerebral cortex. The superficial layers of the entorhinal cortex receive input from the hippocampus and the deeper layers of the entorhinal cortex receive output from the hippocampus [19]. In the test phase, when the hippocampal model received the preconditioned input model from the

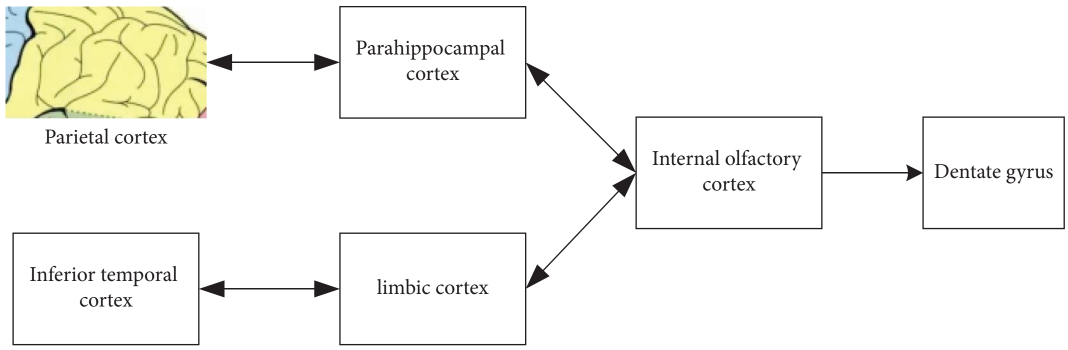

Figure 1: Information storage and extraction process of the hippocampal model.

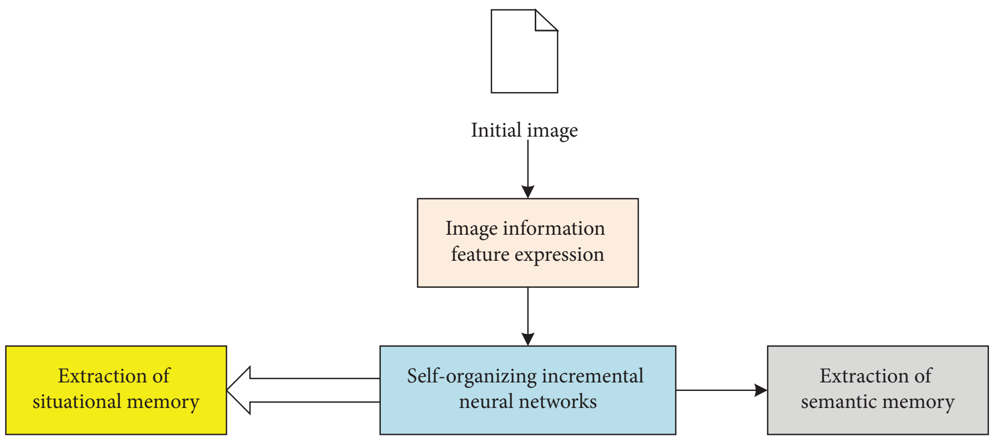

Figure 2: A cognitive neural computing framework for image information storage and extraction.

entorhinal cortex, the model was able to reactivate the CA3 model corresponding to this whole element, which strengthened the weights of the entorhinal cortex circuitry and strengthened the CA3 loop. As the weights became stronger, reactivation extended from the representation of the CA3 element to the representation of the CA1 element and from the representation of the CA1 element to the representation of the output element of the entorhinal cortex. Thus, the hippocampus is able to retrieve the full version of learned patterns from the entorhinal cortex in response to partial cues. Figure 1 shows the information storage and extraction process of the hippocampal model.

In the framework of the CLS model, two models are included: the hippocampus and the medial temporal cortex. The two models have their own division of labor. The hippocampal model is responsible for quickly remembering specific events, and the medial temporal cortex model is responsible for slowly learning semantic information in the environment. This framework model is used to interpret large amounts of human and animal data and is considered one of the most sophisticated models in the field of neural networks. Combined with the CLS model framework, a cognitive neural computing framework for image information storage and extraction is designed, as shown in Figure 2.

The self-organizing incremental neural network can perform online incremental learning, and each learning and training will update the weights of the nodes in the network, and the result of the update is to make the network structure more in line with the distribution of data. These properties are fully consistent with the assumptions of the CLS model for the function of the medial temporal cortex. Therefore, a neural network was used to simulate the online incremental learning ability of the medial temporal cortex. Since the various structures and functions of the hippocampal model in the CLS model conform to the physiological structure, they were not changed. In this framework, the neural network models the medial temporal cortex for storing and retrieving semantic memories, and the hippocampus model for storing and retrieving episodic memories. The hippocampus has two functional modes, encoding mode and retrieval mode, corresponding to the learning phase and the testing phase, respectively. In encoding mode, CA1 activation was driven primarily by neural networks; in retrieval mode, CA1 activation was primarily driven by memory traces stored in CA3.

The feature extraction stage of image processing is the basic link of image retrieval. Only correct description and extraction of features can ensure the accuracy of recognition. When storing and extracting image information, the establishment of the image information feature expression model is the key factor that determines the quality of image information storage and extraction results. The establishment of the image information feature expression model is to complete the storage and extraction of image information by extracting the characteristics of the image itself and expressing it in a certain way. When establishing the image information feature representation model, it is necessary to consider which features to represent the image, and good features can not only reduce the complexity of the operation but also improve the accuracy of extraction; the second is to determine the features of the image. Then, how to accurately extract these features, a good feature extraction method can play a multiplier effect with half the effort. Due to the complexity of image information, there is no unified feature selection method so far. Generally speaking, for different applications, different feature extraction and selection methods are used. However, qualified image features should have the following characteristics: (1) distinction: features should have a large amount of identifying information, unique to the target image, and have good distinguishability; (2) reliability: refers to the stability within the class, the same type of images must have similar or the same eigenvalue; (3) autonomy: refers to the autonomy between types, the characteristics of each type should be different, and the difference between the types is greater than the difference within; (4) low-dimensional number: with the increase of the feature dimension, the amount of operation also increases, and it should be converted into a low-dimensional feature space as much as possible.

For an image, there are usually three methods to extract local features in the image. (1) Dense sampling: the most commonly used dense sampling method is the uniform segmentation method. This method divides the image sample into several small blocks uniformly according to a certain scale and then uses a large set of small image blocks obtained as the features of the image, and these features are also the basis for the generation of the dictionary. There is also a commonly used dense sampling method: the sliding window method. This method takes the small image block contained in the window as a local area by sliding the window, and the size and content of the local area change with the window size and the pixel interval of window sliding. In the obtained set of small image patches, this method may result in partial overlap between the small image patches. (2) Machine sampling: the random sampling technique is to randomly sample an image and describe it as a feature. The disadvantage of this algorithm is that random sampling will cause local areas in the image to be in the background, thereby affecting the expression of objects in the image. (3) Detection and sampling of points of interest: the development history of local features was looked at. The invariance of local features is a hot research topic and the key to its development. The invariant feature of an image is the invariant representation or description of the image, that is, the essence of an image different from another image, including rotation invariance, scale invariance, affine invariance, and illumination invariance. In real life, humans only focus on the target of interest, and the same is true for local features. The coordinate position of the point of interest in the image is also what people care about, and the size and shape of its neighborhood are also taken into account.

There are two types of image feature extraction methods: global and local feature extraction. The former is generally used to describe the content of the entire image, such as color, texture, and shape, and is obtained by counting all points in the image. Since it contains the entirety of the image, it is somewhat robust to random noise. However, due to the changes of illumination, scale, rotation, and other changes in the image, the global features will also change, which cannot be accurately described. For this reason, the neural network algorithm in intelligent computing is introduced in this study. The so-called intelligent computing is to use the laws of nature, especially the laws of the biological world, to solve problems through simulation. It has the characteristics of self-learning, self-organization, and self-adaptation and has been widely used in various fields.

Artificial neural network has the ability of self-organization and self-learning. It can receive training samples and discover the rules and inherent characteristics of the data in the training samples during the learning process. With these rules, the neural network can quickly classify and identify when the subsequent test samples are input. The feedback characteristics of the neural network, that is, the inappropriate characteristics of the data characteristics are obtained from the training samples and fed back to its characteristic group, and the reasonable correction makes its intelligence perform better; the neural network has parallel processing capability, which makes it possible to process its data quickly and make real-time processing possible. Because the number of nodes in the neural network is limited, there is too much information to learn and memorize in real life. This means that the neural network may need to use limited weights to store unlimited input information, that is, use the competitive learning theory to store information. The artificial neural network can well approximate any complex nonlinear relationship so that its performance is improved, thereby improving the fault tolerance and storage capacity of the system.

The basic unit of the PCNN neural network model is the pulse-coupled neuron. These basic units are connected to each other to form a single-layer two-dimensional locally connected feedback network. Each neuron consists of three parts: the receptive field, the modulation field, and the pulse generating part. The PCNN model does not need to be trained and has self-organization ability, and the threshold changes dynamically according to the time and the results of surrounding neurons. Spike-coupled neurons are the basic components of spike-coupled neural networks. Numerous parameters of pulse-coupled neurons have nonlinear relationships that restrict each other. The relationship between the parameters of the PCNN model determines its different characteristics from general neural networks: variable threshold characteristics, synchronous pulse firing phenomenon, capture characteristics, dynamic pulse firing phenomenon, automatic wave characteristics, and comprehensive spatiotemporal characteristics. PCNN has the characteristics of synchronous pulse release, and PCNN has good rotation invariance, scale invariance, and

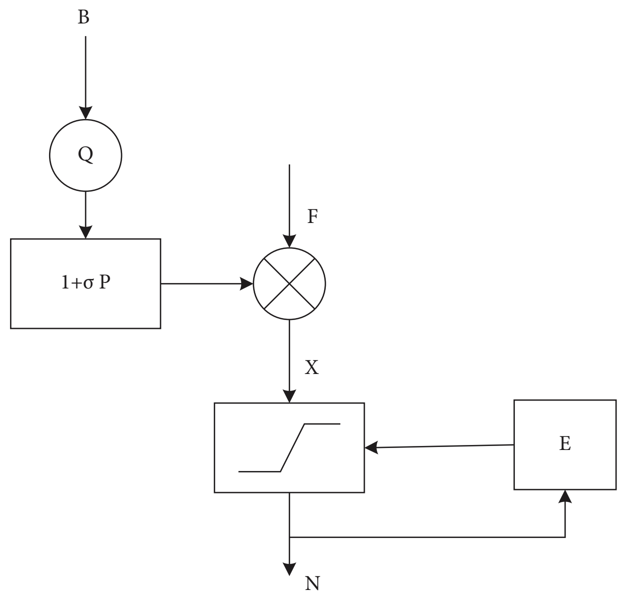

Figure 3: Basic structure of a single pulse-coupled neuron.

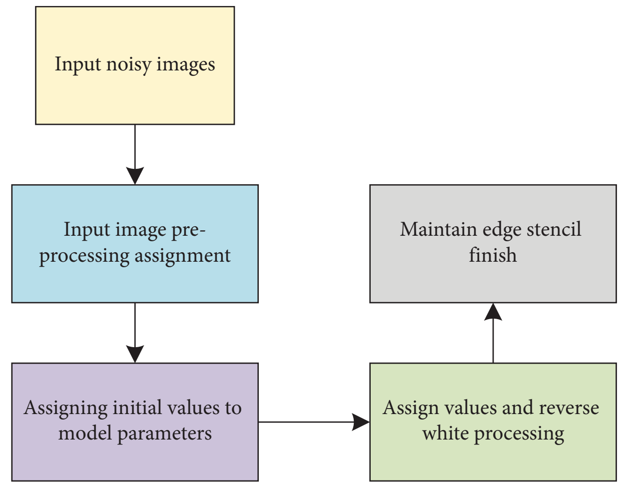

Figure 4: Basic steps of the algorithm.

signal intensity invariance in image processing. The basic structure of a single pulse-coupled neuron is shown in Figure 3.

The neurons of PCNN have the characteristic of variable threshold decay, which decays exponentially with the passage of time, and the internal activity term of the neuron is greater than the current dynamic threshold and emits pulses. The firing cycle of each neuron is different. In a certain period, the dynamic threshold of each neuron will decay with a certain period and release pulses at various moments, showing a dynamic pulse distribution. When the neuron is in motion, the visible wave propagates in a similar way to a wave, and its propagation direction is similar to that of the wavefront neuron. This is the dynamic pulse distribution and waveform characteristics of PCNN. The distribution and capture characteristics of synchronous pulses are exactly in line with the distribution of dynamic pulses and the characteristics of automatic waves. The former has static characteristics and the latter has dynamic characteristics. The pulse signal in the static state is the spatial characteristic of the input signal, while the output of the dynamic signal is the time-domain characteristic of the signal. At the same time, the number of pulses' output reflects the spatial nature of the system. At different moments, the number and sequence of output pulses reflect the temporal characteristics of the input signal, which is the comprehensive spatiotemporal characteristics of PCNN. The synchronous pulse firing phenomenon and the capture feature in the PCNN features constitute the static properties of the PCNN model. The dynamic pulse firing phenomenon and the autowave characteristics constitute the dynamic characteristics of the PCNN model.

During image processing, the details and edges of the original image are preserved as much as possible. In image noise, impulse noise occupies a large proportion. In this study, PCNN and edge preservation algorithm are combined to eliminate noise and extract edges. Figure 4 shows the basic steps of the algorithm.

The following is the relevant formula of the algorithm of PCNN combined with the algorithm of preserving the edge:

$$\begin{aligned}
F_{uv}[b] &= U_{uv},\\
P_{uv}[b] &= \sum_{kp} Q_{uvkp} N[b-1],\\
X_{uv}[b] &= F_{uv}[b]\left(1+\varepsilon P_{uv}[b]\right),\\
B_{uv}[b] &= \begin{Bmatrix} 1, X_{uv}[b] > E[b-1], \\ 0, X_{uv}[b] \le E[b-1], \end{Bmatrix},\\
E_{uv}[b] &= e^{-\delta} E_{uv}[b-1] + Y_E B_{uv}[b],
\end{aligned} \tag{1}$$

where U_{uv} is the gray value of the corresponding pixel point, F_{uv} is the input to the neuron, P_{uv} is the connection input of the neuron, X_{uv} is internal activity items, and E_{uv} is dynamic threshold,

$$\mathrm{ME} = \frac{1}{A \times B} \sum_{m=0}^{A-1} \sum_{n=0}^{B-1} \left[\mathrm{f}(m,n) - \overline{f}(m,n) \right]^2, \tag{2}$$

where $f(m,n)$ is the original image,

$$\begin{aligned}
\sigma_0 &= \sum_{a=0}^{t} \frac{aL_a}{q_0},\\
\sigma_1 &= \sum_{a=t+1}^{A-1} \frac{aL_a}{q_1},
\end{aligned} \tag{3}$$

where σ is the average gray value,

$$\begin{aligned}
\sigma &= \sum_{a=0}^{A-1} aL_a,\\
h &= q_0\left(\sigma_0 - \sigma\right)^2 + q_1\left(\sigma_1 - \sigma\right)^2,
\end{aligned} \tag{4}$$

where h is between-class variance and σ is the overall average gray level of the image,

$$h(t^*) = \arg\left\{ {}_{0 \le t \le A-1}^{\mathrm{Max}} \left[h(t) \right] \right\}, \tag{5}$$

where $h(t^*)$ is segmentation threshold,

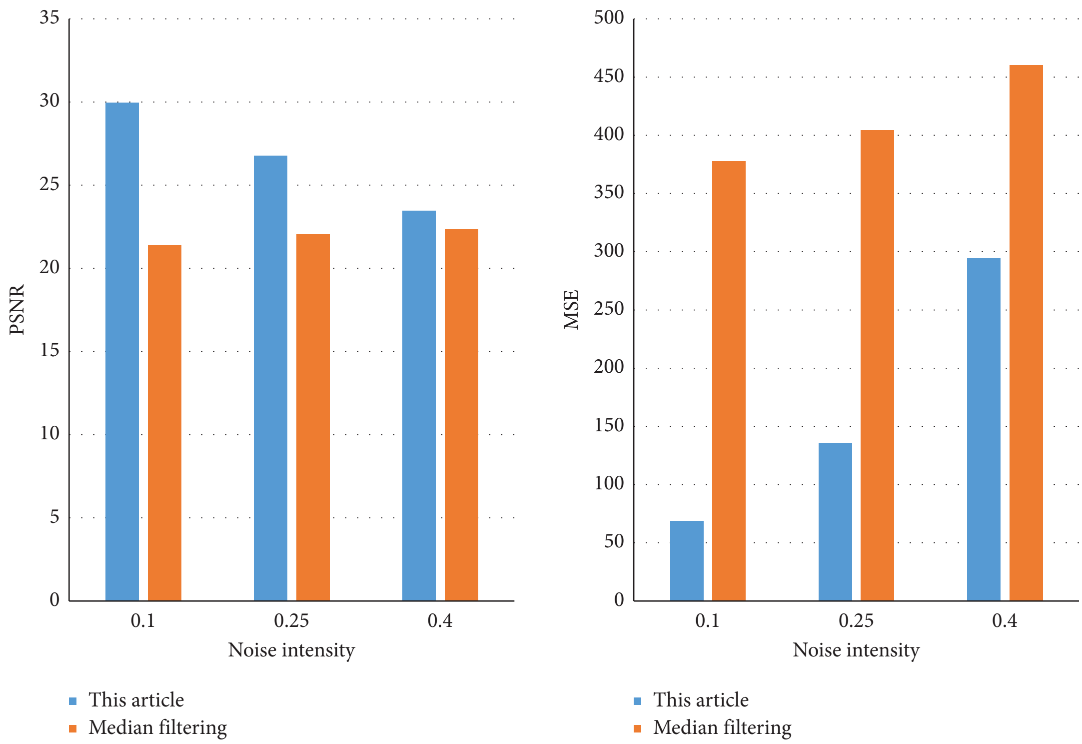

FIGURE 5: Comparative results of indicators.

$$t^* = \operatorname{Arg}(\operatorname{Max}(\varphi(t))), \tag{6}$$

where t^* is optimal threshold,

$$L = -L_0 \log_2 L_0 - L_1 \log_2 L_1, \tag{7}$$

where L is the entropy value after segmentation,

$$\mathrm{e} = \frac{1}{2} \sum_{\mathrm{o}=1}^{\mathrm{w}} \left(\mathrm{s}_0(\mathrm{k}) - \mathrm{no}_0(\mathrm{k})\right)^2, \tag{8}$$

where e is the error function.

$$\begin{aligned} X_l &= \sum_{v=1}^{l} Q_{lv} m_v, \\ Y_l &= X_l - \theta_l, \\ N_l &= \tau(Y_l), \end{aligned} \tag{9}$$

where $X_l$is the result of a linear combination, θ_l is bias threshold for neuron units, and τ is the activation function

3. Cognitive Neural Computational Modeling Experiments

As a comparison, the image denoising method in this study is processed by median filtering. Compared to the algorithm used in this work, both methods perform postprocessing on the processed image to remove the edges to verify the effect of the simulation experiments. To better describe the effect of noise removal, besides the subjective evaluation, the objective evaluation, root mean square, and signal-to-noise ratio are also used to describe the two parameters. Figures 5 and 6 show the index comparison results.

As the figures show, in both experiments, the signal-to-noise performance of the algorithm in this study is larger than that of the median filtering method. The mean square mistake of the proposed algorithm is less than that of the median filtering method, and the experimental data reflect the superiority of the algorithm. From the simulation outcomes, it is clear that the algorithm in this study retains more details than the median filtering method in terms of the visual effect of the subjective evaluation criteria.

In order to verify the effectiveness of the cognitive neural computing model for image information storage and extraction based on intelligent computing, in all experiments, the selected images are processed in grayscale. After the image information is learned, the recognition test experiment is carried out first, and a test stimulus image is given to determine whether it has been learned. As shown in Figures 7 and 8 and Table 1, the accuracy of the database recognition test is shown.

From the above data, it can be seen that the recognition ability of the model in this study is very strong. When the learned sample images are relatively small, the model will still make mistakes in judgment. However, when the learned sample images reach a certain number, the model can basically judge all the learned images. When the number of samples of learning images is 5, the time required by the method in this study is 236 s, the time required by the median filtering method is 475 s, and the time required without the algorithm is 2212 s. The method in this study greatly improves the use efficiency.

In a recall test trial, what the model does is to extract the semantic information of the test stimulus image, that is, the name of the test stimulus image itself. Similar to the recognition

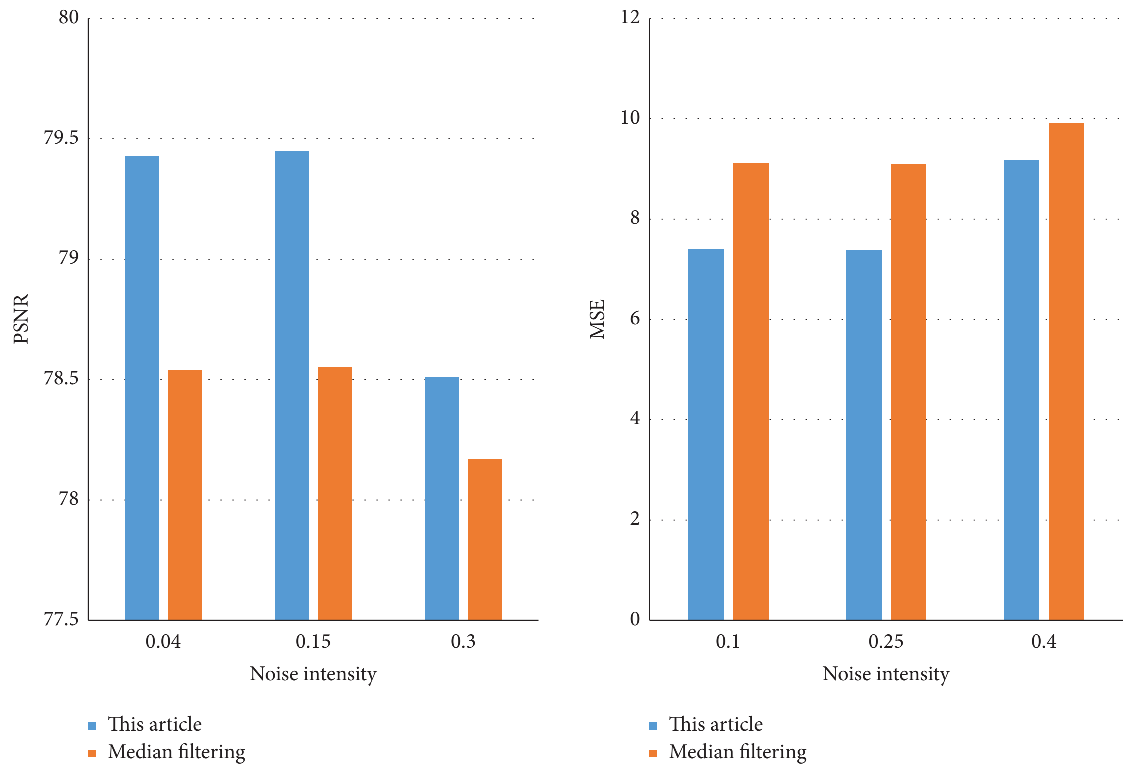

Figure 6: Comparative results of indicators.

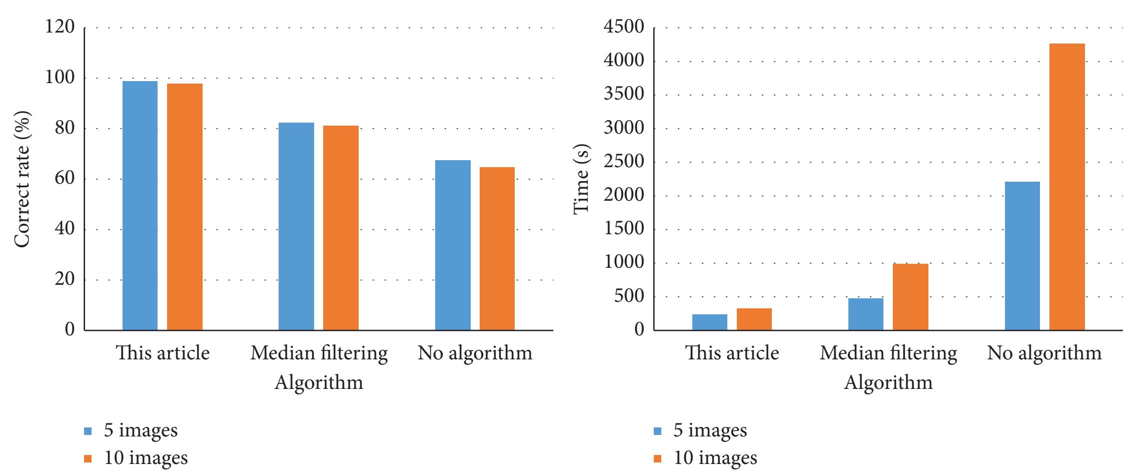

Figure 7: Correctness of database recertification test.

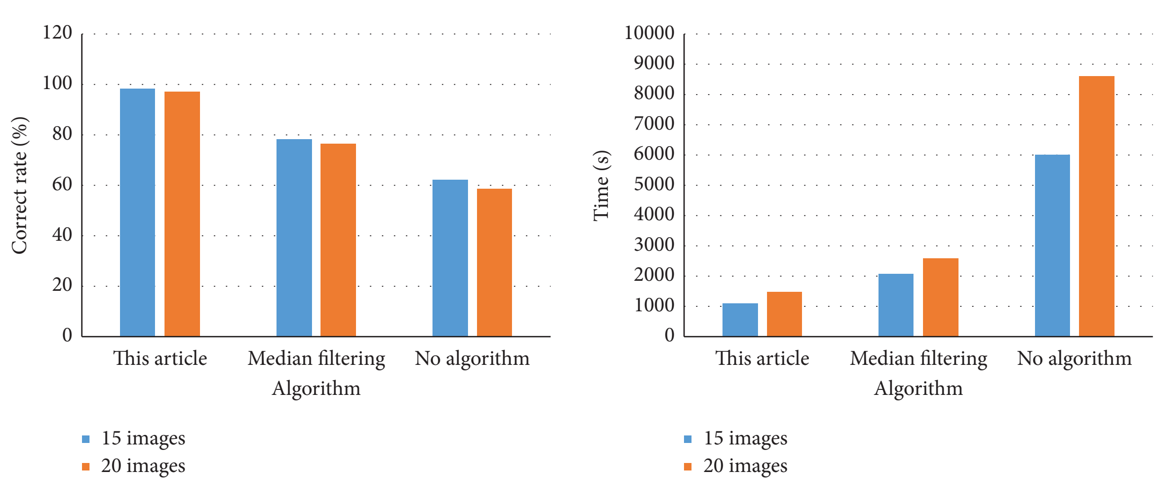

Figure 8: Correctness of database re-identification test for 15 and 20 images.

Table 1: Correctness of database re-identification test for 25 and 35 images.

Number of learning image samples	This article		Median filtering		No algorithm	
	Correct rate (%)	Time (s)	Correct rate (%)	Time (s)	Correct rate (%)	Time (s)
25	100	2345	72.4	3192	61.3	9772
30	100	2689	71.8	3810	62.7	9964
35	100	2927	70.6	4537	60.9	10124

Table 2: Correctness of recall tests.

Number of learning image samples	This article		Median filtering	
	Correct rate (%)	Time (s)	Correct rate (%)	Time (s)
5	63.2	457	42.1	2192
10	65.6	1076	46.8	4197
15	68.5	2049	49.2	6152

Table 3: Correctness of recall tests.

Number of learning image samples	This article		Median filtering	
	Correct rate (%)	Time (s)	Correct rate (%)	Time (s)
20	72.8	2568	43.2	8574
25	74.2	3214	45.2	9762
30	83.2	3894	43.1	9987

test, the recall test results may also be misjudged; that is, the name of the test stimulus image may be incorrectly recalled, or the learned image may be judged as unlearned. As shown in Tables 2 and 3, the accuracy of recall test is shown.

From the data in the table, it can be seen that the recall results of the method using the algorithm of this study to select features are higher than the median filter recall results, but the learning time is much lower than the median filter method. This shows that the method of selecting some features in the algorithm in this study can effectively represent the features and improve the operation speed.

4. Conclusion

The purpose of learning and memory is to understand how people store and retrieve information based on past experience. The development of cognitive psychology, cognitive neuroscience, physiological anatomy, and other disciplines has further developed some information processing mechanisms in the human brain. Based on a review of the physiological basis of brain memory mechanism, this study introduced some representative memory models based on cognitive psychology and combined them to simulate the memory function of the medial temporal lobe and hippocampus of the brain. This study made preliminary predictions in this regard. Due to the limitation of the source of information and academic standard, omissions are inevitable in this paper's research. At the stage of analysis of the current situation, the analysis is not comprehensive, reflecting only the changes of the relevant indicators, lacking judgment, and analysis of the internal enterprise; in theory, it has not been understood in depth. When the number of images increases and the size of the dictionary increases, the computational overhead required for its learning and encoding becomes larger and larger, far from being comparable to that of humans. Therefore, improving and proposing new sparse coding algorithms is also one of the focuses of our future research. This study summarized the study in his section and pointed out the shortcomings of this study. It is necessary to consider improving the hippocampal model, simulate various structural functions of the hippocampal model, and complete the rapid retrieval of episodic memory.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Disclosure

The authors confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

Conflicts of Interest

The author declares that there are no potential conflicts of interest in our paper.

Authors' Contributions

The author has seen the manuscript and approved to submit to the journal for publication.

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