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Hybrid Novel Machine Learning and Computer Vision Research

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Abstract: With the increasing demands of society on the level of human intelligence, people are more demanding of human-like intelligent robots that can work normally in highly complex environments, perform non-specific tasks and have a high degree of initiative. This paper mainly discusses the research of hybrid novel machine learning and computer vision. This paper firstly describes the human-computer interaction based on "vision". The "visual" human-computer interaction system refers to the basic principle of human visual information, using a computer with a camera to detect and identify the user's actions through non-traditional input devices, and then perform automatic human-computer interaction in two-dimensional or three-dimensional space. Then, the machine learning prediction algorithm is introduced. Finally, the experimental design and result analysis of the robot vision learning method based on the human brain-like cognitive computing model are carried out. The experimental results show that from the final recognition rate, the recognition rate of the growing long-term memory is 93.2%, which is higher than the 91.4% of the VNAIL algorithm. After the robot has a growing long-term memory that works in conjunction with working memory, it can independently master visual cognitive ability, and incrementally store and update knowledge. Intellectual development, classification and recognition abilities are improved over methods without long-term memory.

1. Introduction

Since the emergence of the emerging discipline of artificial intelligence in 1956, its field has continued to expand, involving expert management systems, automatic theorem proving, machine learning, model recognition, machine vision, human natural language understanding, artificial intelligence robots, etc. It has an important influence on the development of today's science and technology, especially modern information science, control science and technology, brain science and technology, and spiritual science and technology. At present, most of the robots with relatively perfect technology and mature use live in special environments and are designed for special tasks. Due to the increasing requirements of human beings on the level of intelligence, people also increasingly demand human-like intelligent robots that can work in highly complex environments, perform non-specific tasks and have a high degree of independence.

In the field of robot research and development, the main purpose of proposing a cognitive thinking system is to better solve the obstacles and problems that cannot be overcome by traditional research and development methods. Thereby, the aforementioned various defects can be effectively solved, and the intelligence level of the robot can be improved, even approaching the level of human cognitive intelligence. This paper discusses the research on hybrid novel machine learning and computer vision, with a view to making certain contributions to the field of machine intelligence.

The innovation of this paper is reflected in the introduction of human-computer interaction based on "vision", and the machine learning prediction algorithm is given. Machine learning methods generally fall into three categories: supervised teaching, unsupervised teaching, and semi-supervised teaching. In conclusion, the study focuses on researching and analyzing a robot vision learning method based on the cognitive computing model of the human brain.

2. Related Work

According to the research progress at home and abroad, different scholars also have certain cooperative research in machine learning and computer vision. Wang J X introduces a machine learning approach that utilizes data-driven and physics-based methods to estimate the discrepancies in Reynolds stress modeled by RANS (Reynolds-averaged Navier-Stokes equations). This approach leverages modern machine learning techniques, specifically random forests, to train a difference function on baseline flow data. Subsequently, this trained model can be employed to estimate the Reynolds stress difference in new fluids[1]. Zhang J introduced a machine learning classifier in which computations are performed in a standard 6TSRAM array, which stores machine learning models. The peripheral circuit implements a mixed-signal weak classifier through the columns of SRAM, the training algorithm implements a strong classifier through boosting, and overcomes circuit non-ideality by combining multiple columns [2]. Malta T M employs a unique and innovative logistic regression algorithm, known as OCLR (one-of-a-kind logistic regression), to extract sets of transcriptomic and epigenetic features from non-transformed pluripotent stem cells and their differentiated progeny. By utilizing OCLR, this study enables the identification of previously unknown biological mechanisms linked to dedifferentiated oncogenic states [3]. In a comprehensive review, Butler K T summarizes the recent advancements in machine learning within the field of chemical science. The article discusses machine learning techniques that are well-suited for addressing fundamental research challenges in this domain, along with outlining the future direction of this field. The author envisions a future where artificial intelligence will play a pivotal role in accelerating the design, synthesis, characterization, and application of molecules and materials [4]. Barbu A introduces a novel and efficient learning approach that incorporates sparsity constraints by systematically eliminating variables according to specific criteria and schedules. Empirical results demonstrate that the proposed method surpasses other cutting-edge techniques in regression, classification, and ranking tasks, while maintaining computational efficiency and scalability [5]. Ioannidou A conducted a survey on the application of deep learning methods on 3D data and categorized them based on their usage. The findings revealed that systems that utilize 2D views of 3D data generally perform better than voxel-based depth models. However, the performance can be improved with more layers and extensive data augmentation. As a result, larger datasets with higher resolutions are necessary [6]. However, these scholars did not discuss the research of hybrid novel machine learning and computer vision, but only discussed its significance unilaterally.

3. Hybrid Novel Machine Learning and Computer Vision Research Methods

3.1 Human-computer Interaction Based on "Vision"

"Vision" human-computer interaction recognizes actions through input devices, and then performs two-dimensional or three-dimensional automatic human-computer interaction. In this process, the camera captures the physical target in the surrounding environment, converts the resulting image into a digital signal and transmits it to the computer [7]. Figure 1 shows the camera-based visual interaction process. The computer can process and understand the "visual" signal, which includes the orientation and motion state of the extracted target through measurement and interpretation, and interactive monitoring [8].

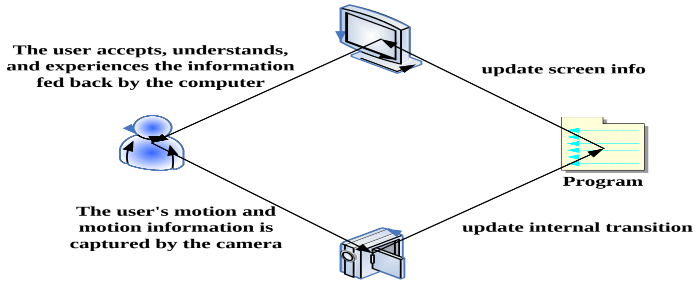

Figure 1 Camera-based visual interaction process

Human-computer interaction based on "vision" is one of the main communication methods between the user and the operating system. Users need to issue commands, requests, questions, wishes and goals to the operating system, and correspondingly, the operating system also needs to respond, provide requests, operating system status information, etc. [9]. One might also imagine this communication process as a series of exchanges. Since the user and the operating system are not in the same programming language, the user interface must also be able to act as a translator. But in fact, it also includes several translation processes. First, the user converts the target into motion, and then converts the physical motion into an electronic form acceptable to the operating system through input and output devices. Finally, the operating system interprets this information according to the current operating system status [10]. Since the operating system usually uses the same method to reflect the input mode of all users, there needs to be an exchange between the entry and the exit - also known as the transfer function. To communicate input and output messages to users, the operating system first needs to convert the information into a numerical display representation. Then it is converted into visual perception information that all users can accept through the output device, and the user converts this perception information into meaningful semantic expressions. The exchange between entry and exit is the well-known control-display mapping. Figure 2 shows the intelligent computer vision interaction.

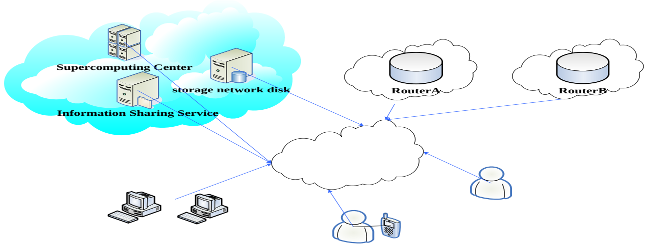

Figure 2 Interaction for intelligent computer vision

3.2 Machine Learning Prediction Algorithms

Methods of computing machine learning generally fall into three categories: supervised teaching, unsupervised teaching, and semi-supervised teaching.

Supervised teaching refers to the process of using the function value obtained by the existing corresponding relationship to obtain the corresponding output from a certain input data. Commonly used regression analysis problems, all use this learning method. Commonly used calculations include support vector machine calculations, Bayesian calculations, etc.

All training samples input by unsupervised machine learning have no obvious identification, and the learning patterns formed by them are only to infer some internal structure of the sample data.

The main difference between semi-supervised teaching and fully-supervised teaching is that some of the input training samples are marked and some are not.

In real-world applications, the most common are supervised and unsupervised instructional model designs. Four typical supervised classification algorithms will be briefly described below.

(1) Support vector machine algorithm

Supports the most compact partition mode in vector machines and is the best interval divider. Assuming that the threshold is 0, we determine the category of the sample a_n according to the positive or negative value of $f(a_n)$. Therefore, the interval from a sample point to the classification surface is $\delta_n = b_n(u^R a_n + y)$ and is always positive. Further, the geometric interval of the classifier can be obtained as $\varphi = \frac{|f(a_n)|}{\|u\|}$. In order to maximize the target geometric interval, it can be converted to solve the following optimization problem:

$$min\ \frac{1}{2}\|u\|^2 \tag{1}$$

$$subject\ to\ \ b_n\big((u^R a_n + y)\big) - 1 > 0, n = 1, \cdots, p \tag{2}$$

The maximum b between geometries is achieved here, where $u \in D^p$ and $y \in D$ are parameters that control the classification surface. The dual form of the above optimization problem is derived using the Lagrangian function:

$$max\ \ K = \sum_{n=1}^{p} \tau_n - \frac{1}{2}\left(\sum_{n,m=1}^{p} \tau_n \tau_m\, b_n b_m a_n^R a_m\right) \tag{3}$$

$$subject\ to\ \ \sum_{n=1}^{p} b_n \tau_n = 0, \tau_n \geq 0\ n = 1, \cdots p \tag{4}$$

Where the Lagrangian coefficient τ_n is the solution of the optimization problem.

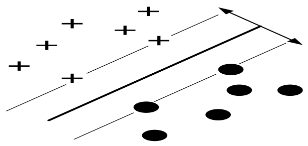

Figure 3 Linear classifier

Due to the presence of noise in real-world data, the feature space is often not linearly separable. In Figure 3, a linear classifier is depicted. To strike a balance between model performance and generalization, the introduction of slack variables allows for the tolerance of fewer error points and outliers. This approach helps to handle the noisy nature of the data and improve the overall performance of the model.Finally, transform the optimization problem into:

$$min\ \frac{1}{2}\|u\|^2 + E\sum_{n=1}^{p} \vartheta_n \tag{5}$$

$$subject\ to\ \ b_n\big((u^R a_n + y)\big) \geq 1 - \vartheta_n\ \vartheta_n > 0, n = 1, \cdots, p \tag{6}$$

Among them, E represents the penalty coefficient. Likewise, the above optimization problem can be transformed into the following dual question using Lagrange multipliers:

$$max\ \ K = \sum_{n=1}^{p} \tau_n - \frac{1}{2}\left(\sum_{n,m-1}^{p} \tau_n \tau_m\, b_n b_m a_n^R a_m\right) \tag{7}$$

$$subject\ to\ \ \sum_{n=1}^{p} b_n \tau_n = 0{,}0 < \tau_n < E\ n = 1, \cdots p \tag{8}$$

Solving the above problems, solve the coefficient τ_n, and get the optimal classification plane. The above is the main idea of SVM to deal with classification problems.

(2) K-nearest neighbor algorithm

The KNN algorithm, short for K nearest neighbor calculation, is a compact machine learning algorithm widely employed in various applications such as face recognition and disease monitoring. It is known for its simplicity and effectiveness in pattern recognition tasks. It is worth noting that the training that does not appear in KNN is also a typical representative of "lazy learning", and its training phase is the process of storing data.

The core idea of the KNN classifier is to have a training sample set, and to know the labels of all the data information of the training sample set. If there is no standard type of data information in the input, the distance characteristics of the input data are first obtained and compared with each data information characteristic of the training set. Generally, the distance is regarded as the characteristic of comparison. Then, the K tags closest to the data information are obtained in the training set, and the number of tags with the highest frequency among the K closest data information is calculated, which is regarded as the type of the comparison input data.

Usually K is used to select the number of nearest neighbor samples, because its selection method is very flexible, and a small K means that the modeling complexity is high, and it is easy to produce overfitting. A large K makes the overall modeling more single, and the approximation error also increases during machine learning. In actual calculation, the correct value of K is generally selected by means of cross-checking. The overall process of the KNN algorithm is shown in Figure 4.

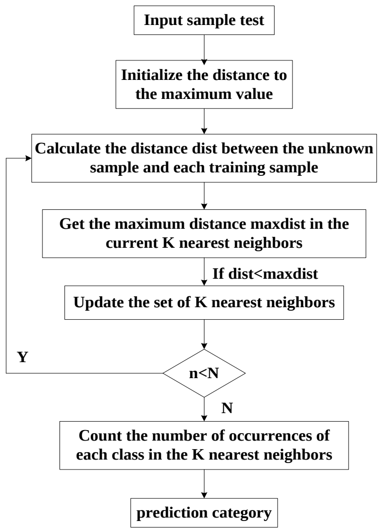

Figure 4 Flow chart of KNN algorithm

(3) Artificial Neural Network

Artificial neural network is a multi-disciplinary application field integrating brain science and technology, neuropsychology and information technology. The main goal is to let the computer perform autonomous learning to imitate the thinking method of the brain, so that the machine can generate the corresponding artificial intelligence. According to the difference in the topological structure of the connection between neurons and the difference in teaching methods, it has been deduced to a completely different neural cell network model. BP neural network is a hierarchical reverse transfer neural network system with three or more layers, which is formed by injection layer,hidden layer and transmission layer. As shown in Figure 5, the three-layer BP neural network diagram.

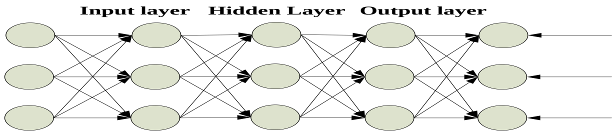

Figure 5 Three-layer BP neural network diagram

Assuming that the number of neurons in the input layer, hidden layer, and output layer are M, N, and H, respectively, the input is $(a_0, a_1, a_2, \cdots, a_{M-1})$, the output of the hidden layer is $(l_0, l_1, l_2, \cdots, l_{N-1})$, and the actual output of the network is $(b_0, b_1, b_2, \cdots, b_{H-1})$, and $(e_0, e_1, e_2, \cdots, e_{H-1})$ represents the expected output of the training sample. Then the output value of the hidden layer unit of the network is:

$$l_n = g(\sum_{m=0}^{M-1} s_{mn} a_m - O_n) \tag{9}$$

The output value of each unit of the output layer is:

$$b_H = g(\sum_{m=0}^{N-1} u_{nh} l_n - O_h) \tag{10}$$

In the back-propagation stage, assuming that the activation function of each level in the BP neural network uses a sigmoid function, that is: $g(net) = \frac{1}{1+e^{-net}}$, the weight correction results of each layer of the network are as follows:

$$\Delta u_{nh} = \varphi O_n (e_h - O_h) g^{`}(net_h) = \varphi O_n (e_h - O_h) O_h (1 - O_h) \tag{11}$$

$$\Delta s_{mn} = \varphi g^{`}(net_n) \sum_{h=0}^{H-1} \beta_n u_{nh} O_m = \varphi O_n (1 - O_n) \sum_{h=0}^{H-1} \beta_n u_{nh} O_m \tag{12}$$

Where φ represents the learning rate; O_m, O_n, O_h represent the output of each layer of neurons.

The BP algorithm uses the forward propagation process to transmit information, and then uses the reverse direction transmission process to improve the weight, and so on and so forth until the deviation is lower than the threshold point or the iteration exceeds the predetermined frequency.

(4) Adaboost

The AdaBoost algorithm is an iterative analysis algorithm that adopts an adaptive approach. The idea is: using the last basic classifier to practice the wrongly classified samples will be valued. After increasing the weight ratio, use the re-weighted samples to practice the next basic classifier. And a new classifier is added in each step, and the iteration will be terminated when the algorithm exceeds the preset threshold. The main process includes:

1) Initializing the weight distribution of training samples.

2) Updating the weights by training a weak classifier. During the training process, if a sample is classified incorrectly, the system will increase its weight, and vice versa.

3) Assigning different weights to each weak classifier trained in the previous step, and sum up to obtain the final strong classifier. Classifiers with lower classification accuracy are given the largest weight, and vice versa.

Specifically, given a training sample $R = \{(a_1, b_1), (a_2, b_2), \cdots, (a_P, b_P)\}$, where the sample $a \in \varphi$, and the sample space $\varphi \in D^p$, b_n belong to the label set {+1,-1}, the specific flow of the algorithm is as follows:

Step 1: initializing the weight distribution of the training samples:

$$C_1 = (u_{11}, u_{12}, \cdots, u_{1n}, \cdots, u_{1P}), u_{1n} = \frac{1}{P}, n = 1,2, \cdots, P \tag{13}$$

Step 2: multi-round iteration process, the number of rounds is expressed as q=1,2,...,Q:

Using the training sample set to learn, its weight distribution is C_{q1}, and obtain the basic classifier:

$$F_q(a): \varphi \to \{-1, +1\} \tag{14}$$

Calculating the classification error rate of $F_q(a)$ on the training sample set:

$$h_q = D(F_q(a_n) \neq b_n) = \sum_{n=1}^{P} u_{qn} N(F_q(a_n) \neq b_n) \tag{15}$$

From the above formula, the error rate h_q of $F_q(a)$ on the training sample set is the sum of the weights of the samples misclassified by $F_q(a)$.

Calculating the coefficients of $F_q(a)$, where δ_q represents how much $F_q(a)$ contributes to the final classifier:

$$\delta_q = \frac{1}{2} log \frac{1-h_q}{h_q} \tag{16}$$

It can be obtained from the above formula that when $h_q \leq \frac{1}{2}$, $\delta_q \geq 0$, and δ_q will become larger as h_q decreases.

Updating the weight distribution of the training sample set, where J_q is the normalization factor:

$$C_{q+1} = \left(u_{q+11}, u_{q+12}, \cdots, u_{q+1n}, \cdots u_{q+1P}\right) \tag{17}$$

$$u_{q+1n} = \frac{U_{qn}}{J_q} exp\left(-\delta_q b_n F_q(a_n)\right), n = 1,2 \cdots, P \tag{18}$$

$$J_q = \sum_{n=1}^{P} u_{qn}\, exp\left(-\delta_q b_n F_q(a_n)\right) \tag{19}$$

Step 3: combining the individual weak classifiers:

$$g(a) = \sum_{q=1}^{Q} \delta_q F_q(a) \tag{20}$$

And then get the final classifier:

$$F(a) = sign(g(a)) = sign\left(\sum_{q=1}^{Q} \delta_q F_q(a)\right) \tag{21}$$

In general machine learning, the number of objects used for research is usually discrete. Although a lot of information can often be obtained by classifying discrete quantitative features, many continuous signals such as bump characteristics, growth rates, inflection points, etc. are missed. That is to say, some functional properties also appear in time space with the number of samples. When studying the number of samples with functional characteristics, the conventional data analysis methods are often ineffective. At this time, the analysis of functional data can be introduced.

4. Mixed Novel Machine Learning and Computer Vision Research Experimental Results

4.1 Experimental Design

This paper comprehensively analyzes the growth-type long-term memory active teaching calculation (VAL-GLTM) driven by the traditional visual stranger, the incremental autonomous visual learning algorithm (VNAIL) driven by the visual stranger, and the method without the internal motivation of the visual stranger (that is, the integration of traditional Q teaching and long-term memory, abbreviated here as Q-GLTM). Their discrimination rates against contextual input information, including cognitive learning time and the number of nodes in the competing layer in the neural network, are compared with the process. Similarly, the active exploration learning ability calculated by VAL-GLTM according to the input information of the situation will be analyzed, and the change trend of the Q value of each situation of the three methods will be analyzed in particular, including the change of strangeness, and clarified the utility and necessity of the change of the internal motivation of visual strangeness on the robot's active exploration and teaching ability.

The experiment will be carried out in the laboratory, allowing the robot to understand and recognize what humans "see" from three different perspectives in the same area. In order to test the independence and incrementality of the incremental visual active teaching calculation based on human intrinsic motivation Q learning, and synchronous data analysis and calculation of the learning effect and discrimination rate of situational cognition. The robot's classified reading image entry scenarios are: aisle, porch, office area. Through the practice-proven VAL-GLTM algorithm, the robot is guided to determine three types of situations, and autonomously explore and master these three types of situations. And it continuously updates the self-learning behavior to accumulate the ability to update cognition, and to analyze the classification characteristics such as the recognition rate of the algorithm.

4.2 Experimental Results and Analysis

Putting the robot in the position of the initial stage of the experiment, let it explore and learn the first three scenarios on its own under the guidance of the algorithm, record the changes of the robot's exploration of each scenario, and analyze its changes with the number of learning steps. As shown in Figure 6, place the robot in the same place as the experiment, let it itself, guided by the algorithm, studied the first three scenarios, recorded the changes in the robot's state during each scenario study, and analyzed changes in its learning rhythm. Robots learn drivers through visual unfamiliarity as an independent study of the situation. In the initial state, the artificial intelligence robot begins to read the script "corridor". In the first few stages of training, the artificial intelligence robot chooses more of these situations, and the more it explores and understands the other two scenarios. As the degree of strangers in the last three scenarios tends to be the same, that is, they have been mastered enough, the selection of these three scenarios in the algorithm also tends to be equal.

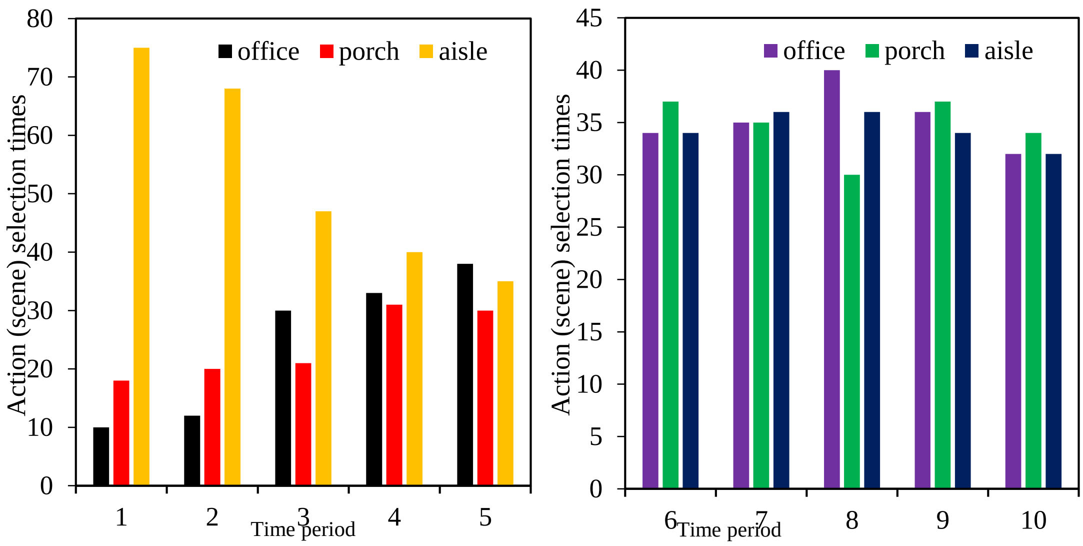

Figure 6 Autonomous exploration and learning of the algorithm robot in this paper

In the VNAIL algorithm, instead of using the growing long-term memory, only the online PCA method is used as the recognizer, and in the process of discussion and learning, people still have visual strangeness and intrinsic motivation. Therefore, the number of scenario selections in the discussion and learning, the Q value of the first three scenarios, and the unfamiliarity of the "aisle" are very similar to those calculated by VAL-GLTM, as shown in Figure 7.

An experimental comparison is made between the algorithm in this paper and the Q-GLTM method, and the Q-GLTM method artificially gives reward information. In the “porch” experiment, registration to the robotic scene selection process gave the largest positive reward, as shown in Figure 8.

In order to further check the algorithm provided by the laboratory, actively seek and induce the ability of artificial intelligence robots to master new knowledge, and copy the new objects given for exploration experiments. When the artificial intelligence robot has mastered all three scenarios, some new objects are placed in the "aisle" scene to record the process of the artificial intelligence robot exploring and practicing autonomously in the following. As can be seen from Figure 9, the computation presented has similar teaching steps to the VNAIL algorithm.

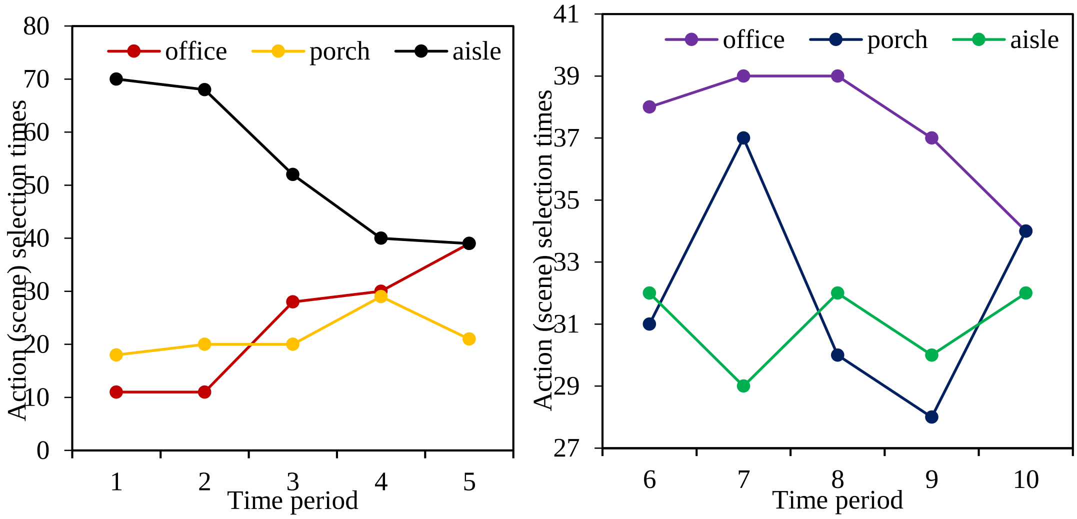

Figure 7 VNAIL algorithm exploration and learning

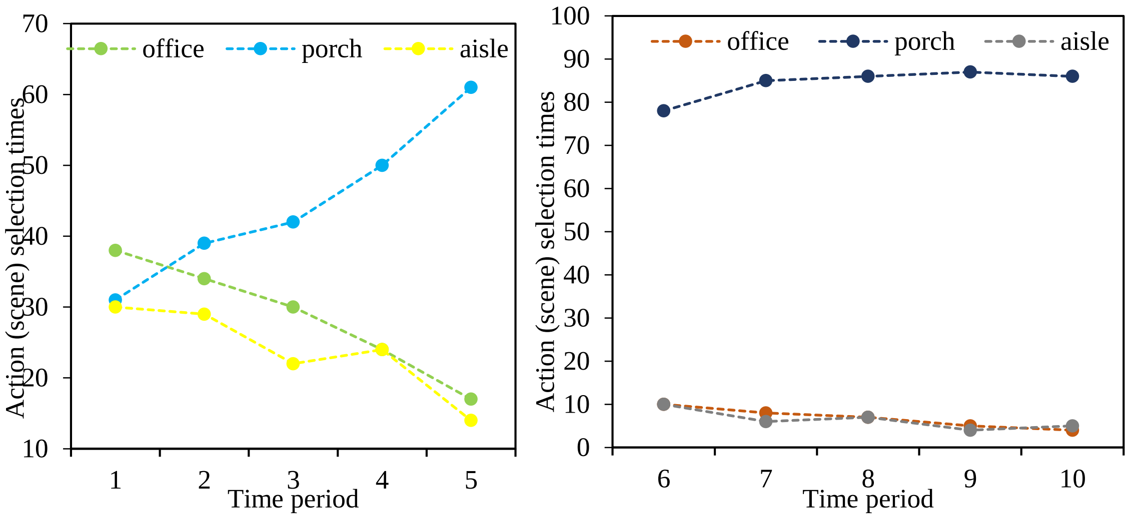

Figure 8 Q-GLTM method for robot exploration and learning

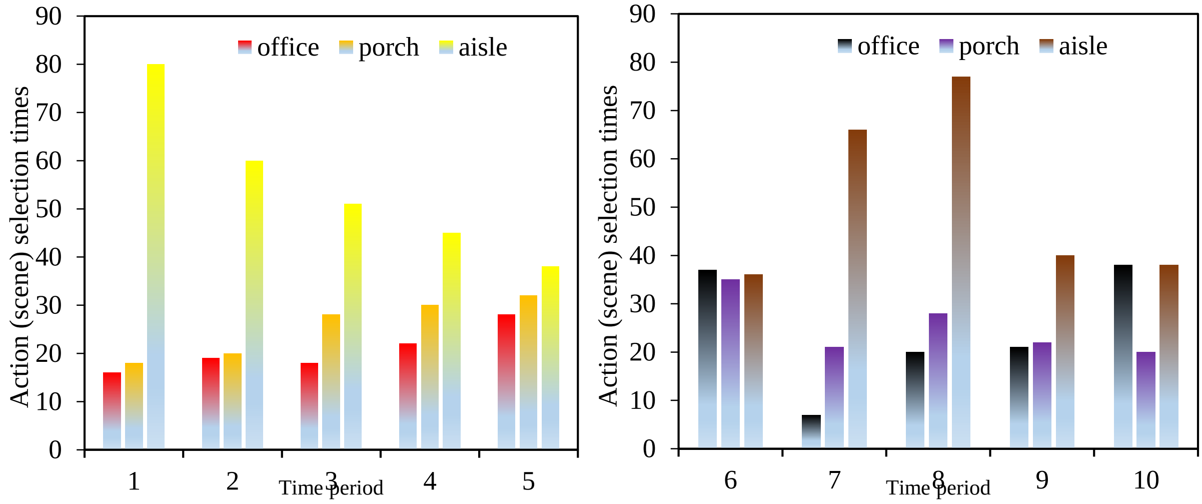

Figure 9 The algorithm actively explores and learns new objects

For each sampling point, the recognition rates of the VAL-GLTM algorithm and the VNAIL algorithm will be compared. The comparison between the two algorithms can be observed from the data presented in Table 1 and Table 2, new types are gradually and serendipitously discovered due to the motivation of low visual unfamiliarity, as well as the efficiency of slow recognition. As a result, the intrinsic motivation greatly improves the activity and learning effect of the algorithm, thereby promoting the improvement of intelligence. At the same time, from the final identification rate, the long-term memory utilization rate during cultivation was 93.20%, which was higher than 91.40% of the VNAIL algorithm.

Table 1 Comparison of recognition rates between VAL-GLTM algorithm and VNIL algorithm (1)

number of samples		100	150	200	250	300
VAL-GLTM	correct number	86	129	181	231	271
	Correct rate(%)	86.9	88.71	90.1	89.3	88.9
ASO-PCA	correct number	72	119	169	209	259
	Correct rate(%)	72.8	79.7	84.9	85.2	88.1

Table 2 Comparison of recognition rates between VAL-GLTM algorithm and VNIL algorithm (2)

number of samples		350	400	450	500
VAL-GLTM	correct number	321	369	419	471
	Correct rate(%)	90.8	93.1	94.1	92.8
ASO-PCA	correct number	309	359	409	461
	Correct rate(%)	90.1	89.8	89.5	90.7

Table 3 VAL-GLTM algorithm and Q-GLTM method comparing learning speed and number of nodes in the competitive layer (1)

number of studies		100	150	200	250	300
VAL-GLTM	Study time (s)	0.099	0.109	0.119	0.141	0.221
	Competitive layer nodes	9	11	13	14	15
ASO-PCA	Study time (s)	0.109	0.131	0.129	0.139	0.201
	Competitive layer nodes	5	6	8	11	13

By comparing the Val-GLTM algorithm with the Q-GLTM method, the changes in time and the number of nodes in the competition layer can be observed, as depicted in Table 3 and Table 4.

Although both methods pertain to neural circuits, there are slight differences. The number of nodes indicates the number of types, while the alteration in the number of segments reflects the variation in the studied class. And so we can find them from the above, visual strangeness and intrinsic motivation enhance the ability of active learning and the effects that it produces from learning.

Table 4 VAL-GLTM algorithm and Q-GLTM method comparing learning speed and number of nodes in the competitive layer (2)

number of studies		350	400	450	500
VAL-GLTM	Study time (s)	0.301	0.351	0.501	0.602
	Competitive layer nodes	15	16	16	16
ASO-PCA	Study time (s)	0.251	0.371	0.492	0.651
	Competitive layer nodes	13	15	15	15

5. Discussion

By simulating the coordinated autonomous learning process of long-term memory and human working memory, visual strangeness-based algorithms can be developed for long-term memory. Experimental results demonstrate that a semi-automatic robot, equipped with a long memory structure learned from working memory, can independently acquire and continuously update visual knowledge in its knowledge base. This approach leads to improved intelligence, classification, and recognition capabilities compared to methods lacking a long-term memory structure. Additionally, the generalization and cognitive expansion abilities of the robot are enhanced as well.

6. Conclusions

For robots designed with traditional artificial intelligence, the intelligent control system faces the limitations of task determination, offline learning, poor scalability, and inability to cope with complex and changeable working environments and tasks. Inspired by the way of human learning, the manifestation of intelligence, and the working mechanism of advanced cognitive intelligence in the human brain, a series of visual learning algorithms based on this model are proposed. In view of the significant impact of the human brain's memory cortex on the human body's advanced perception and developmental capabilities, the growth and long-term memory parts of the simulated memory cortex are also set in the cognitive function calculation model. A growth-type long-term memory active learning algorithm driven by visual strangeness was invented, which introduced the control mechanism of human working memory into the growth-type learning of long-term memory. In this way, what industrial robots have learned through active exploration can be continuously updated into long-term memory, which improves the initiative of knowledge accumulation and intelligent development.

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