Transactions on Computational and Scientific Methods | Vo. 5, No. 2, 2025
ISSN: 2998-8780
https://pspress.org/index.php/tcsm
Pinnacle Science Press

Dynamic Optimization of Human-Computer Interaction Interfaces Using Graph Convolutional Networks and Q-Learning

Qi Sun
Carnegie Mellon University
1067557192sunqi@gmail.com, Pittsburgh, USA

Abstract: With the rapid development of artificial intelligence technology, intelligent human-computer interaction systems have gradually become an important tool for improving user experience and work efficiency. Traditional human-computer interaction interfaces usually rely on static rules and fixed layouts, which are difficult to adapt to the changing needs of users and complex operating environments. To solve this problem, this paper proposes a dynamic interaction interface optimization method based on graph convolutional networks (GCNs) and Q-learning. This method combines the powerful feature extraction capabilities of graph convolutional networks with the adaptive optimization characteristics of Q-learning and can dynamically adjust the layout and response strategy of the interface to meet the needs of different users and environments. First, GCN is used to extract graph structure features from user interaction data to capture the complex relationship between interface elements; then, combined with the Q-learning algorithm, the response strategy of the interface is optimized through reinforcement learning to improve the flexibility and real-time adaptability of the system. Experimental results show that the optimization method based on GCN and Q-learning is superior to traditional static layout methods and deep learning feature extraction methods in terms of user satisfaction, response time, and operating efficiency, verifying the effectiveness of this method in dynamically optimizing interaction interfaces. This study provides a new idea for the intelligent optimization of human-computer interaction interfaces and provides technical support for future applications in smart devices and virtual reality.

Keywords: Dynamic human-computer interaction, Graph convolutional networks, Reinforcement learning, Adaptive optimization.

1. Introduction

In the context of the rapid development of modern science and technology, human-computer interaction (HCI) has become a core area to promote technological innovation and enhance user experience. With the continuous advancement of technologies such as computer vision, natural language processing, and deep learning, the design of human-computer interaction interfaces has gradually become more intelligent and personalized. Traditional human-computer interaction interfaces usually rely on fixed rules and manually designed interaction methods [1], which have served as a solid foundation for many practical applications, such as ATMs, automated customer service systems, and even early adaptive learning platforms. These systems are particularly effective for straightforward tasks where user input and environmental conditions are relatively predictable. For example, a traditional interface might provide a static menu system in a self-checkout kiosk, ensuring reliability and ease of use in controlled retail settings.

However, these rule-based systems often struggle to accommodate complex, nuanced, or rapidly changing user needs. For instance, an automated customer service chatbot operating on predefined decision trees may fail to address ambiguous or multi-layered queries effectively, leaving users frustrated. Similarly, static interfaces may falter in dynamic environments, such as collaborative tools requiring real-time adaptation to diverse user workflows or preferences [2]. The lack of adaptability can hinder user satisfaction and system efficiency, especially as expectations for personalized and context-aware interactions grow.

In order to solve these problems, researchers have begun to try to introduce more flexible and adaptive algorithm models to improve the intelligence level of human-computer interaction interfaces [3]. This paper proposes a dynamic human-computer interaction interface optimization method based on a combination of graph convolutional networks (GCN) and Q-learning, aiming to achieve dynamic optimization and intelligent adjustment of the interaction interface by enhancing the adaptive ability of learning and deep analysis of graph structure data [4].

Graph convolutional networks (GCNs) are a powerful graph neural network model that can effectively process data with graph structures. In traditional neural networks, data is usually input in the form of vectors or matrices [5]. However, in many practical problems, data often have obvious topological relationships, such as user connections in social networks and similarities between items in recommendation systems. In the human-computer interaction interface, the relationship between user behavior and interface elements can also be regarded as a graph structure, and the user's input and feedback are transmitted and converted through the interface elements. Therefore, GCN has a natural advantage in processing this structured data. It can capture the complex relationship between different interface elements through graph convolution operations and extract valuable features from them, providing a more accurate basis for subsequent interaction optimization [6].

However, relying solely on GCN for static feature extraction is not enough to cope with the dynamically changing human-computer interaction needs. With the continuous changes in user behavior and environment, the interactive interface needs to have a certain degree of adaptive ability and be able to adjust and optimize in real-time to provide the best user experience. To this end, we introduced the Q-learning algorithm, which is an adaptive optimization method based on reinforcement learning. Q-learning learns the optimal strategy through interaction with the environment and constantly adjusts decisions through trial and error so that the system can make the best action choice under different states. In the human-computer interaction interface, Q-learning can simulate user operations and feedback, and constantly adjust the layout and response mode of the interface to improve the system's adaptability and intelligence level to user needs [7].

In the scheme proposed in this paper, GCN is combined with Q-learning to form a new dynamic optimization mechanism. Specifically, GCN is responsible for extracting valuable features from the graph structure data of the interactive interface, while Q-learning uses these features to learn and optimize strategies. Through continuous training and adjustment, the system can gradually learn to select the optimal interaction strategy and interface layout under different user scenarios and needs. The advantage of this method is that it can not only use the powerful feature learning ability of GCN to capture the relationship between user behavior and interface elements but also achieve real-time optimization in a complex and changing environment through the adaptive ability of Q-learning, thereby greatly improving the intelligence and flexibility of human-computer interaction.

In general, the research work in this paper provides a new idea for the intelligent optimization of human-computer interaction interfaces. By combining GCN and Q-learning, a dynamic optimization framework is proposed, which can adjust the interactive interface according to the real-time feedback and needs of users to provide a more personalized and intelligent experience. This research not only provides theoretical support for technological innovation in the field of human-computer interaction but also provides new tools and methods for interface design and optimization in practical applications. With the continuous development of artificial intelligence technology and the increasing number of application scenarios, interaction optimization methods based on graph convolutional networks and reinforcement learning are expected to be widely used in various smart devices, virtual reality, augmented reality, and other fields, pushing human-computer interaction technology into a new stage of greater intelligence and efficiency.

2. Related Work

In recent years, with the development of deep learning and graph neural network technology, human-computer interaction research based on these technologies has gradually become a hot topic in academia and industry [8]. Graph neural network (GNN) has been widely used in social network analysis, recommendation systems, intelligent transportation, and other fields due to its advantages in processing graph structure data. In the field of human-computer interaction, researchers have tried to use GNN to model the complex relationship between users and interface elements in order to extract more representative and personalized features from the data. For example, some studies use GCN to analyze user behavior patterns and optimize the layout and interaction process of the interface through graph structure. In this way, GCN can more accurately capture the changes in user needs, thereby achieving a more intelligent and personalized interaction experience [9,10]. However, most of the existing research focuses on the extraction and analysis of static features, lacks sufficient adaptive capabilities, and is difficult to cope with dynamically changing interaction needs.

On the other hand, the successful application of reinforcement learning (RL) in intelligent decision-making and adaptive control has made it an important tool for optimizing human-computer interaction interfaces. Q-learning, as a classic model-free reinforcement learning algorithm, enables the system to learn the optimal action strategy in a constantly changing environment by exploring and utilizing iterative updates of strategies. In the field of human-computer interaction, the application of reinforcement learning has gradually been launched, and many researchers have tried to combine it with traditional interface design methods to improve the system's adaptability and response speed. For example, some work optimizes the response strategy of the user interface through reinforcement learning to improve user satisfaction and interaction efficiency. However, these methods often ignore the intrinsic relationship between interface elements and the complexity of user behavior. Combining reinforcement learning with graph neural networks can give full play to the advantages of both. It can not only learn complex user-interface interaction relationships through graph structures but also use reinforcement learning to achieve dynamic optimization of the interface, thereby improving the intelligence level of human-computer interaction [11].

3. Method

In this study, we proposed a dynamic human-computer interaction interface optimization method based on graph convolutional networks (GCN) and Q-learning. The core idea of this method is to use GCN to extract structural features from the interaction interface and optimize the layout and response strategy of the interface through Q-learning to achieve adaptive and intelligent interaction interface design. Its main architecture is shown in Figure 1.

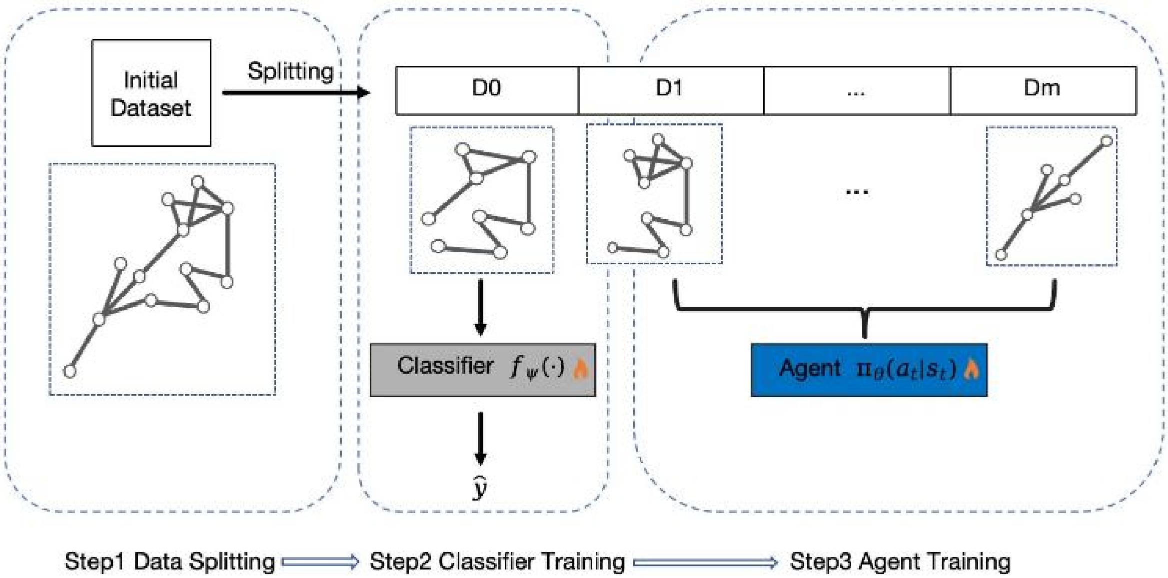

Figure 1. Model overall framework diagram

First, assume that our human-computer interaction interface can be represented as a graph structure, where each node in the graph represents an interactive element (such as a button, input box, etc.), and the edge represents the relationship between different elements (such as physical position relationship, functional dependency, etc.). Let the node set of the graph be $V = \{v_1, v_2, ...v_n\}$ and the edge set be $E = \{e_1, e_2, ...e_n\}$. In GCN, the feature vector of each node v_i is updated through the graph convolution operation. The basic formula of graph convolution is:

$$h^{(k+1)}_i = \sigma(\sum_{j \in N(i)} \frac{1}{c, j} W^{(k)} h_j^{(k)} + b^{(k)})$$

Among them, $h^{(k)}_i$ is the feature representation of node v_i at the k-th layer, $N(i)$ is the set of neighbor nodes of node v_i, $c_{i,j}$ is the normalization constant of edge $e_{i,j}$, $W^{(k)}$ and $b^{(k)}$ are the weight matrix and bias term of the k-th layer respectively, and $\sigma(\cdot)$ is the activation function (such as ReLU). The graph convolution operation aggregates the information of neighbor nodes, allowing each node to learn richer features from the nodes around it, thereby capturing the complex relationship between the elements of the interactive interface.

Next, in order to achieve dynamic optimization of the interface, we introduced the Q-learning algorithm. Q-learning is a method based on reinforcement learning, which aims to learn the optimal strategy through interaction with the environment. Suppose at a certain moment, the system is in state s_t, and action a_t is selected in this state. The system gets an immediate reward r_t and the next state s_{t+1} according to the execution of the action. According to the Bellman equation, the goal of Q-learning is to find the optimal strategy by updating the Q value function $Q(s,a)$:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) +$$
$$\partial[r_t + \gamma \max_a Q(s_{t+1}, a') - Q(s_t, a_t)]$$

Among them, ∂ is the learning rate, γ is the discount factor, r_t is the immediate reward, and $\max_a Q(s_{t+1}, a')$ is the maximum Q value when the optimal action F is executed in the next state a'. Q-learning continuously updates the Q value function, allowing the system to select the optimal action in different interaction states to achieve the optimal interface response strategy.

In this method, GCN is used to extract features from the graph structure, and Q-learning optimizes the response strategy of the interactive interface based on these features. Specifically, the system uses the node features extracted by GCN as input, combined with the current state s_t and action a_t, to learn the optimal interface adjustment strategy under the framework of Q-learning. During the training process, the system continuously adjusts the layout, button position, response order, etc. of the interface through interaction with the user, making the user's operation smoother and more intelligent. In this way, the system can adapt to different user needs and environmental changes to achieve dynamic interface optimization.

In general, the combination of GCN and Q-learning makes this method have strong adaptability and intelligent characteristics. GCN provides rich feature information by capturing the complex relationship between interface elements while Q-learning dynamically optimizes the response strategy of the interactive interface through reinforcement learning. This combination can not only improve the flexibility of the system but also achieve a more personalized and intelligent user experience.

4. Experiment

4.1 Datasets

In this study, we used a public real-world dataset, "Microsoft Research's Surface Gesture Dataset". This dataset contains gesture data of users interacting with touchscreen devices, which is suitable for studying gesture recognition and human-computer interaction interface optimization. The dataset records different gestures performed by users when using touchscreen devices, covering operations such as clicking, sliding, zooming, and rotating. Each sample includes the temporal features of the gesture and the corresponding label, which can provide valuable input for analyzing and optimizing the touch interface.

This dataset includes a large amount of user interaction data, covering a variety of different device touch operations. Each interaction operation records the dynamic changes of the gesture through sensors, including coordinates, speed, acceleration, and other information at each moment. These data can be regarded as graph structure data with time series, where each gesture action can be regarded as a node, and the temporal and spatial relationships between gestures can constitute the edges of the graph. In this way, we can use graph convolutional networks (GCNs) to extract effective features from them, and then optimize the response and layout of the interface.

To evaluate the performance of our model, we used standard evaluation indicators such as accuracy, recall, and F1-score. The rich gesture categories and corresponding operation behaviors provided by the dataset can effectively train the model, thereby realizing dynamic adjustment and optimization of the interactive interface. In addition, the diverse user behaviors in the dataset also provide challenges for the generalization ability of the model, ensuring the reliability and validity of the research results. With the support of this dataset, combined with the framework of GCN and Q-learning, we can better simulate and optimize real human-computer interaction scenarios.

4.2 Experimental Results

In order to verify the effectiveness of the dynamic human-computer interaction interface optimization method based on GCN and Q-learning proposed in this paper, we designed a comparative experiment and compared it with the traditional human-computer interaction optimization method. In the experiment, we used different optimization algorithms, including a static layout method based on classic rules and a static feature extraction method based on deep learning. By comparing the performance of each method in terms of interactive interface response speed, user satisfaction, and operation efficiency, the advantages of this method can be fully evaluated. The experimental results show that the method combining GCN and Q-learning can significantly improve the intelligence and adaptability of the interactive interface, especially in dynamic adjustment and response to user-personalized needs. The experimental results are shown in Table 1.

Table 1: Experimental results

Model	**User satisfaction (%)**	**Response time (seconds)**	**Operation efficiency (times/minute)**
Static feature extraction method of CNN	75.13	0.45	22.15
Static layout method	80.32	0.38	24.63
Ours	89.58	0.32	28.61

From the experimental results, the optimization method based on GCN and Q-learning proposed in this paper shows obvious advantages in all three evaluation indicators. First, in terms of user satisfaction, our method reached 89.58%. Compared with the traditional static layout method (80.32%) and static feature extraction method (75.13%), users are more satisfied with the optimized interactive interface. This shows that the dynamic optimization strategy combining GCN and Q-learning can better meet the personalized needs of users and improve user experience.

Secondly, in terms of response time, the response time of our method is 0.32 seconds, which is shorter than 0.38 seconds of the static layout method and 0.45 seconds of the static feature extraction method. This means that our model can respond to user input more quickly, reduce the delay of interface operation, and thus improve interaction efficiency. Fast response time is crucial to improving the user's smooth experience, especially in high-frequency interaction application scenarios, which can significantly reduce the user's waiting time.

Finally, in terms of operation efficiency, our method can complete 28.61 operations per minute, which is significantly higher than the static layout method (24.63 times) and the static feature extraction method (22.15 times). This result shows that the model combining GCN and Q-learning can support user operations more efficiently, reduce redundancy and errors in operations, and improve overall interaction efficiency. In summary, the experimental results show that the optimization method based on GCN and Q-learning has significant advantages in improving user satisfaction, accelerating response speed, and improving operation efficiency, which verifies the effectiveness and innovation of this research method. In addition, this paper also shows the centrality experimental results of the graph structure used. These results are shown in detail in Figure 2, which clearly presents the centrality distribution of each node in the network through different node colors and shapes. These experimental results can help us fully understand the importance of different types of nodes in the graph and provide data support for subsequent analysis.

The centrality measurement results in Figure 2 not only reveal the influence of each node in the graph structure but also reflect the relative relationship between nodes in the network and the path of information flow. Through these experimental results, we can analyze the characteristics of the graph structure more deeply and provide a scientific basis for optimizing the connection method of the graph and improving the efficiency of information transmission.

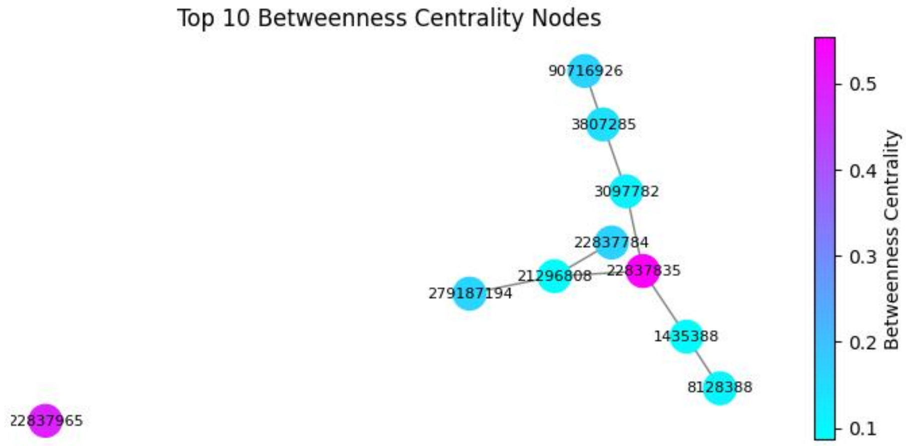

Figure 2. Overall graph structure and structural metrics

As can be seen from the figure, the size and color of the nodes represent their closeness centrality, that is, the average shortest path distance between the node and other nodes. Nodes with lighter colors indicate that they have higher closeness centrality, which means that these nodes are in a more central position in the network and can transfer information with other nodes more quickly. In contrast, nodes with darker colors have lower closeness centrality, indicating that they are at the edge of the network and have lower efficiency in information transfer.

In addition, the distribution of nodes shows a certain structure, indicating that the topology of the network may have a certain degree of aggregation. The distance between the central nodes is close, indicating that they are closely connected to each other in the network and can better play the role of information transfer and network. Based on these analyses, the layout of nodes in the network can be further optimized to improve the efficiency of information dissemination or strengthen the functions of specific nodes.

At the same time, we also give the overall graph structure used, as shown in Figure 3.

As can be seen from the figure, the shape and color of the nodes represent different centrality measures, including degree centrality, betweenness centrality, and closeness centrality. Most of the nodes in the figure are small gray dots, indicating that they do not perform particularly well in these centrality measures. However, some nodes are highlighted by different shapes and colors, indicating that their centrality performance in the network is more prominent. For example, red circular nodes represent nodes with a higher degree of centrality, which have more connections and may be important hubs in the network. In addition, the green square nodes represent nodes with a higher degree of centrality and betweenness centrality. These nodes not only have more direct connections in the network but also play a bridging role in the information transmission process, which can effectively connect different network areas and promote the rapid spread of information. Due to their strong connectivity, these nodes have an important impact on the stability of the network and the flow of information.

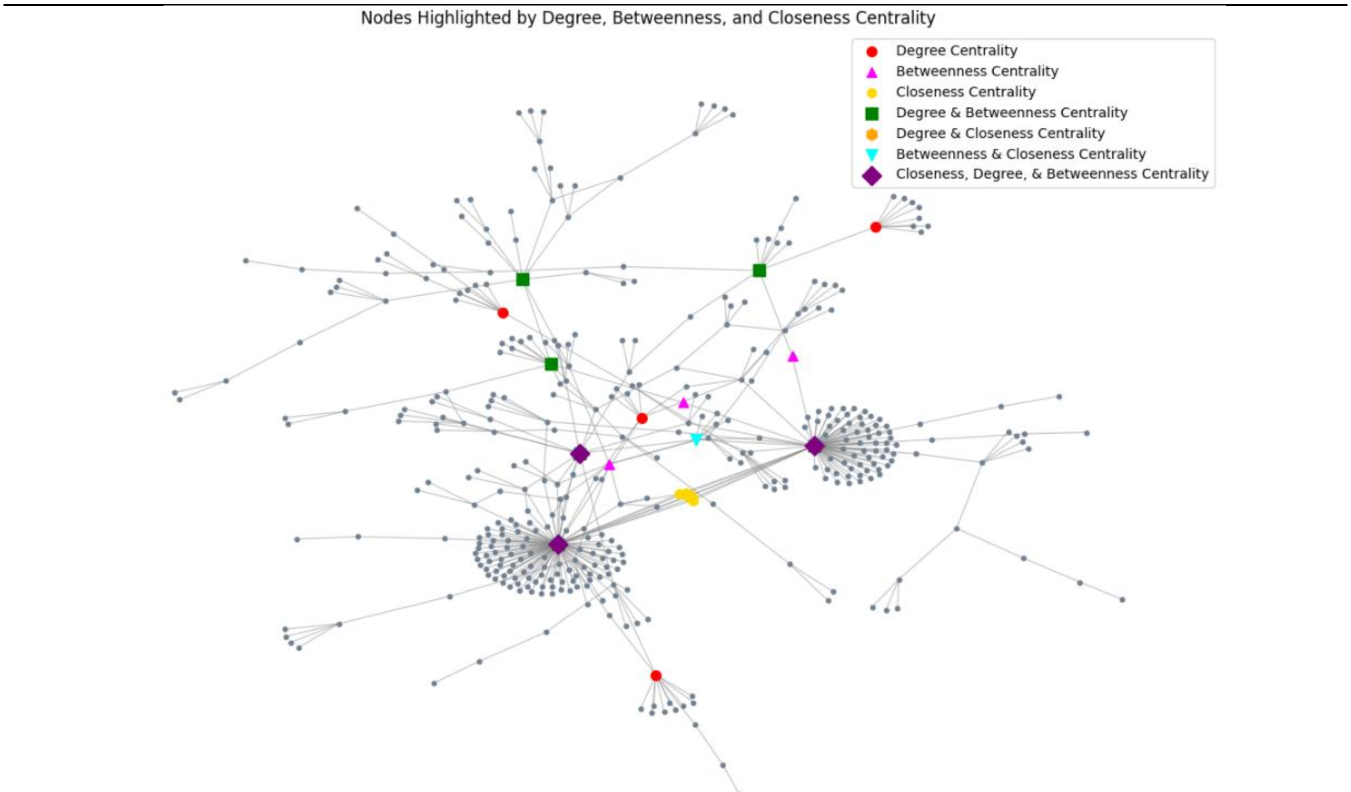

Figure 3. Overall graph structure and structural metrics

The purple diamond nodes perform well in terms of closeness centrality, degree centrality, and betweenness centrality. This means that these nodes play multiple important roles in the network, which can simultaneously promote the flow of information and enhance the stability of the network. Due to their excellent performance on multiple levels, these nodes are likely to be key nodes in the network and are essential for optimizing and controlling the function of the entire network. The figure also marks multiple different types of centrality intersection nodes, such as triangular nodes representing high betweenness centrality and yellow nodes representing high closeness centrality. The existence of these nodes highlights the complex interactions between different centralities in the network structure, indicating that there are not only highly connected nodes in the network but also many nodes that act as "intermediaries" for information transmission, reflecting the diversity and complexity of the network as a whole. This structural analysis helps us to deeply understand the topological characteristics of the network and how to optimize and utilize these nodes in different tasks. Finally, we also show the experimental results after reinforcement learning optimization, including the centrality measurement in the figure. These results are shown in Figure 4, which clearly shows the changes in the centrality of network nodes before and after optimization.

The centrality measurement shown in Figure 4 not only reflects the adjustment of the network structure after reinforcement learning optimization but also helps us understand the impact of optimization on the relationship between nodes. Through these experimental results, we can more intuitively evaluate the effectiveness of reinforcement learning optimization in improving network performance.

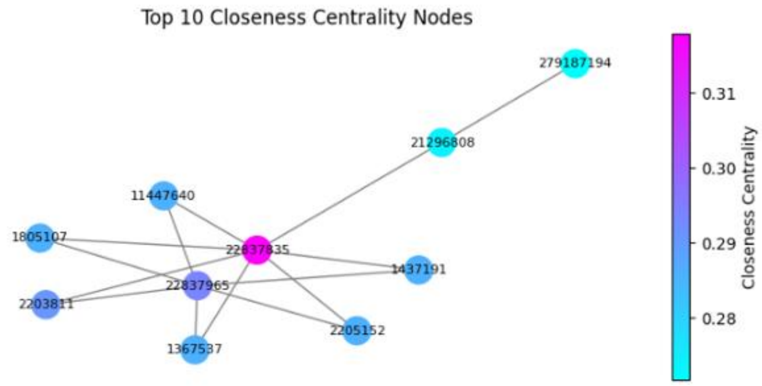

Figure 4. Graph centrality metrics after reinforcement learning

From the experimental results in the figure, after reinforcement learning optimization, the top 10 nodes with high proximity centrality are shown in the figure. These nodes have large proximity centrality values in the network, showing superior information dissemination capabilities. The size and color of the nodes show their importance in the figure. Larger nodes indicate that they have higher proximity centrality, which means that they are closer to all other nodes in the network and can exchange information with other nodes in the network more quickly. These nodes are usually the core part of the network and can affect the transmission efficiency of the entire network.

From the color change, when the node's proximity centrality value is high, the color tends to be light blue and green, while the node with a lower proximity centrality value is dark blue or purple. This color mapping not only highlights the centrality of the node in the network but also intuitively shows the key nodes in the information flow. Through the change of color, users can more clearly identify the nodes with important influence in the network. These nodes with high proximity centrality play a more important role in the network and can play a key role in the process of information dissemination and resource sharing. The optimized network structure, by strengthening these key nodes, can more effectively support the rapid dissemination of information and the efficient sharing of resources, and improve the function and efficiency of the entire network.

In addition, the figure shows the connection relationship between nodes, which not only reflects the relative position of the nodes but also reveals the interdependence between nodes in the network. Through the optimization of reinforcement learning, the connection between nodes is closer, and the connection between core nodes is enhanced, thereby improving the overall network coordination efficiency. The optimized network shows higher robustness and better information dissemination ability. In general, after reinforcement learning optimization, the nodes in the graph show more obvious centrality differences, indicating that the network can more effectively adjust the importance of nodes after learning and promote efficient information dissemination. By optimizing the centrality metric, reinforcement learning not only improves the connectivity of key nodes but also enhances the overall performance of the network, providing effective support for tasks such as network optimization and resource scheduling.

5. Conclusion

This paper proposes a dynamic human-computer interaction interface optimization method based on graph convolutional networks (GCN) and Q-learning. The effectiveness of this method in improving user satisfaction, response speed, and operation efficiency is verified through experiments. Experimental results show that combining the graph structure feature extraction capability of GCN with the adaptive optimization strategy of Q-learning can effectively improve the intelligence level of the interactive interface, enabling it to better respond to user needs and optimize user experience. Compared with traditional methods, the method proposed in this paper shows higher flexibility and efficiency in dynamic interactive environments.

From a user experience perspective, the proposed method has the potential to revolutionize interaction design by creating systems that adapt seamlessly to user preferences and real-time behavior. For example, in an e-learning platform, the system could dynamically adjust the interface based on a student's progress, preferred learning style, or even detected frustration levels, offering a truly personalized experience. Similarly, in customer service applications, such as virtual assistants, the system could analyze user intent in real time to adjust dialog flows, prioritize critical tasks, and deliver a more empathetic, human-like interaction. These adaptive capabilities not only enhance usability but also promote deeper engagement and satisfaction by reducing cognitive load and improving task completion rates.

However, although the optimization method proposed in this paper has shown significant advantages, there is still room for further improvement. For example, when dealing with more complex interaction modes and more diverse user needs, the current method may face challenges in computational complexity and real-time response. Future research can further improve the performance of the model by introducing more efficient graph convolutional network structures, optimizing the training process of Q-learning, or combining other reinforcement learning methods. Additionally, given the growing importance of multimodal interaction-such as voice, gesture, and eye-tracking inputs-future work could investigate how to seamlessly incorporate multimodal data to create interfaces that respond to users in a natural and intuitive way. For example, in the context of augmented reality (AR), a system could adapt its visual overlays based on gaze patterns, hand movements, and environmental context, ensuring a smooth and efficient interaction. How to expand the application scope and applicable scenarios of the model while maintaining system efficiency is still a problem worthy of in-depth exploration.

Looking ahead, with the continuous advancement of artificial intelligence technology, optimization methods based on deep learning and reinforcement learning are expected to be applied in more fields. Especially in the fields of virtual reality, augmented reality, and smart homes, the interaction mode between users and smart devices will become more complex and personalized. Intelligent systems have the potential to redefine how users interact with devices and environments. For instance, a smart home system could proactively adjust lighting, temperature, or even room layouts based on the behavior and preferences of different household members, creating a more comfortable and intuitive living experience. Moreover, improving the intelligence of human-computer interaction interfaces can not only enhance operational efficiency but also foster a stronger sense of trust and emotional connection between users and systems.

Therefore, further improving the intelligence level of the human-computer interaction interface can not only provide users with a more efficient operation experience but also promote a more natural and efficient human-computer collaboration. Future research can explore how to better integrate multiple sensor data and user behavior analysis to achieve a more intelligent interaction interface. In short, the research in this paper provides a new idea for the optimization of interaction interfaces based on GCN and Q-learning and demonstrates its potential to improve user experience and system performance. With the continuous development of technology, this deep learning-based optimization method is expected to be promoted and implemented in a wider range of application scenarios in the future, laying the foundation for the further development of intelligent systems.

References

[1] Srilakshmi N, Radha N. Multi-View Human Action Recognition using Adaptive Optimization Algorithm with Skeleton Based Graph Neural Networks[C]//2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE). IEEE, 2024: 1-7.

[2] S. Duan, "Systematic Analysis of User Perception for Interface Design Enhancement," Proceedings of the 2024 Journal of Computer Science and Software Applications, vol. 5, no. 2.

[3] Gokulnath S, Ponraj A, Krishna B. Motion Control Using Brain Computer Interface Utilizing GCNs-Net with BILstms[C]//2024 4th International Conference on Data Engineering and Communication Systems (ICDECS). IEEE, 2024: 1-7.

[4] Li M, Chen K, Bai Y, et al. Skeleton action recognition via graph convolutional network with self-attention module[J]. Electronic Research Archive, 2024, 32(4): 2848-2864.

[5] Mishra R, Satpathy R, Pati B. Interpretable AI in Medical Imaging: Enhancing Diagnostic Accuracy through Human-Computer Interaction[J]. Journal of Artificial Intelligence and Systems, 2024, 6(1): 96-111.

[6] Karthik A, Manikandan M, Dinesh P, et al. Advancing Human Computer Interaction Through a Hybrid EEG-Based Emotion Recognition System[C]//2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE). IEEE, 2024: 01-06.

[7] Wang Y. A Point-2s reinforcement learning biomimetic model for estimating and analyzing human 3D motion posture[J]. Image and Vision Computing, 2024, 144: 104927.

[8] Rao D S, Rao L K, Bhagyaraju V, et al. Advancing Human Action Recognition and Medical Image Segmentation using GRU Networks with V-Net Architecture[J]. International Journal of Advanced Computer Science & Applications, 2024, 15(2).

[9] D'Amelio A, Lin J, Ramel J Y, et al. Guest Editorial Emerging Trends and Advances in Graph-Based Methods and Applications[J]. IEEE Transactions on Emerging Topics in Computing, 2024, 12(1): 122-125.

[10] He Z. RETRACTED ARTICLE: An Improved Human-Computer Interaction Content Recommendation Method Based on Knowledge Graph[J]. International Journal of Human–Computer Interaction, 2024: 1-12.

[11] Yi M. Revolutionizing interaction: the role of artificial intelligent conversation agents in human-computer interaction[C]//Fourth International Conference on Signal Processing and Machine Learning (CONF-SPML 2024). SPIE, 2024, 13077: 192-201.