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Artificial Intelligence Recommendation System Model for Military Cabin Space Environment Design

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ABSTRACT

This paper proposes an artificial intelligence-based recommendation model for military cabin space environment design schemes to satisfy military cabin operators with a comfortable and efficient working environment and improve the safety and health of the operators. Each key design feature is used to extract the interactive relationship between the operator and the cabin design. Through the neural network, the operator's psychological comfort is interactively matched with the cabin space environment factors. As result, the interactive artificial intelligence cabin space environment design scheme recommendation system is recommended and established. The results showed that the method can optimize the environmental design of military cabins, alleviate some of the design complexities associated with military cabins, and improve the physical and mental health of operators. Additionally, by using an AI-based recommendation system for cabin space environment design, engineers can reduce the time and resources required to design military cabins, resulting in faster turnaround times and lower costs.

1. Introduction

The military cabin refers to a special type of semi-enclosed or fully enclosed workplace with certain limitations and special performance requirements in a certain complex environment. There is a relatively complex man-machine-environment system in its space. It is mainly used in military deep-sea submersible cabins, military vehicle-mounted command systems and other fields. The complex environment of military cabins contains various factors, including color, temperature, air quality, noise and light, etc. The above factors are considered in the design process, including comfort, functional safety, and other issues. Therefore, under the premise of meeting the strict requirements of the military, it is a difficult task to design a complex and interactive military cabin environment. Thus, it is required to consider several design factors such as work reliability, physical

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and mental health in order to develop a sustainable development cycle for military cabin. At this stage, research related to the spatial environment design of military cabins is very crucial, especially related to thermal comfort, noise reduction, and lighting. For example, Zhou *et al.,* (2021) explored the influence of temperature and humidity on the thermal comfort of soldiers in military cabins [1]. The research result showed the temperature and humidity within a specific range is affecting the thermal comfort of soldiers. Besides that, from the same research mentioned the noise level is one of the significant factors that affects the space environment of military cabins. According to another similar research by Malhari *et al.,* (2021) found that high noise levels in the cabin environment led to increased stress levels and cognitive decline, thereby affecting the overall effectiveness of soldiers [2]. Blanch *et al.,* (2021) explored the effect of lighting conditions on the vision of soldiers in military compartments, and found that low lighting levels lead to vision loss, which affects the ability of soldiers to perform critical tasks [3]. The development of artificial intelligence systems in various industries, including aviation and navigation, has brought about innovative changes. Applying machine learning algorithms to cabin design can optimize the design of various aspects of the cabin, such as temperature and airflow, to provide comfort and efficient cabin environment. The application of artificial intelligence in the design of military cabins is limited, and most systems are designed for civilian and commercial cabins. However, military cabins have unique requirements that are different from civilian and commercial cabins. Veitvh *et al.,* (2021) explored the application of artificial intelligence in the design of military cabins and proposed an artificial intelligence-based method to optimize the design process. The research showed that artificial intelligence can improve the efficiency and accuracy of military cabin design and reduce costs. In addition, the research also showed that the artificial intelligent can ensure that the final product meets the needs of military personnel [4]. Russo *et al.,* (2022) proposed an artificial intelligence-based method to optimize the design of military cabins, considering various factors such as cabin layout, comfort, and safety. The study also indicated that the proposed method could reduce the design cost and improve the design process efficiency [5].

As conclusion, the above-mentioned cabin design research has the application of artificial intelligence theory, however it only focuses on a single factor of the cabin environment to meet the comfort and safety of the cabin personnel, and does not comprehensively analyze the cabin environmental factors. Therefore, it is necessary to develop research on the environmental design of cabin space complexity. Therefore, this paper applies the innovation of deep learning theory in the field of artificial intelligence to the environmental design of military cabins that interactively matches the operator's psychological comfort with the complex environmental characteristics of the cabin through establishment of an interactive artificial intelligence recommendation system. Through the system, it quickly obtains the optimal adaptability between psychological comfort and the cabin environment and the establishment of an interactive artificial intelligence military cabin space environment design scheme recommendation system to reduce the time and resources required to design military cabins, thereby shortening the delivery time and reducing costs. A cost-effective way to optimize the cabin environment and improve operator safety and health [6-10].

2. Methodology

2.1 Construct the Overall Framework of The Military Cabin Environment Design Model

As the most prominent and concentrated area of the human-machine interface, the military cabin has a direct impact on the psychological and physiological comfort and work efficiency of the operators. Therefore, in the design of the military cabin environment, it is helpful to solve the problem through accurate design schemes which include Operator’s comfort and efficient work issues. In order to improve the accuracy of the designer's design plan and shorten the time and cost of designing the comfort of the military cabin environment, it is an effective way to be recommended to the designer. It is necessary to find a suitable and efficient recommendation system to assist designers in their design work in order to fulfill the preferences from operators. Based on the fact that the military cabin is a complex man-machine-environment system, a recommendation system that can obtain the recommended system the interaction between the operator and the cabin environment is needed. This paper will discuss the use of each key design of the operator and the cabin environment through an independent scoring model featuring of extracting the composition of the interaction between the operator and the cabin design, and obtaining the feature vector model through the prediction neural network from the historical and current perspectives. Extracting the operator’s psychological optimum comfort and the key features of the cabin environment through the gradient descent method to train the neural network subsequently establish an interactive artificial intelligence recommended system to obtain the optimal adaptability between the operator's psychological comfort and the cabin environment [11-16].

In this paper, the feature vectors of the operator and the cabin environment need to be trained before the neural network is initiated. In order to predict the score of an operator for a specific cabin environment, the feature vector corresponding to the operator and the cabin environment needs to input into the predicted value that is obtained from the neural network [17]. Therefore, the model can be divided into two main stages. The frame diagram of the research process of the military cabin system model is shown in Figure 1. In the feature learning stage, the feature learning model generates the corresponding operator and cabin environment feature vectors according to the operator-operator and cabin environment-cabin environment co-occurrence relationship through the operator's scoring matrix. The eigenvectors of the operator and the cabin environment are generated independently of each other, and their generation processes correspond to (a) and (b) in Figure 1, respectively. In the neural network training phase, the final score is obtained by the score prediction neural network by using the Recurrent Independent Mechanisms (RIM) feature vector of the operator and the cabin environment obtained from the previous pre-training as input, and is calculated layer by layer in the network [18]. This process corresponds in Figure 1(c) is to get an accurate prediction, and the neural network needs to be trained. As shown in Figure 1(d), where the target label of the network is the score of the corresponding operator in the scoring matrix for the specific cabin environment. Through training, the network can capture the interaction between the operator and the cabin environment.

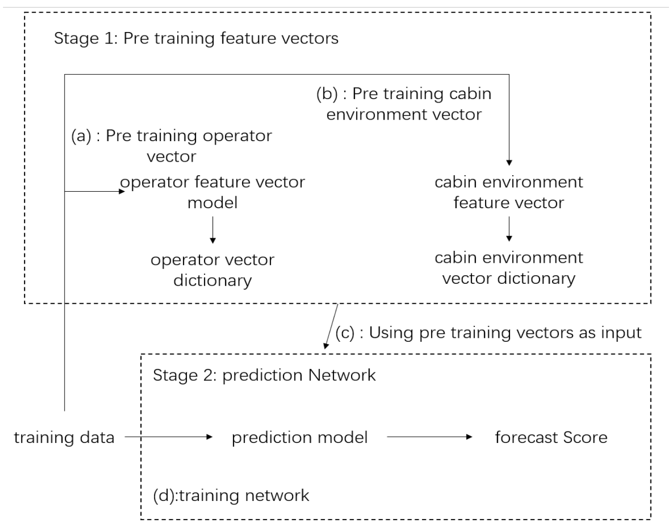

Fig. 1. Research process of military cabin system model

2.2 Pre-trained Feature Vector Model

Considering that the different ratings between the operator-operator and the cabin environment-cabin environment are ignored, the RIM is used to represent the status of the cabin environment under different ratings by using different feature vectors. The process of cabin environment feature vector in RIM is shown in Figure 2.

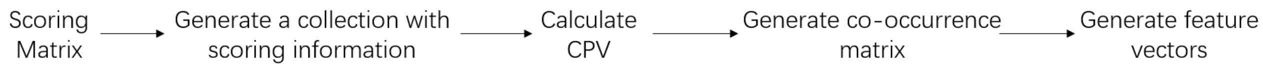

Fig. 2. Cabin environmental feature vector process diagram

In RIM, each cabin environment will be represented by K (different cabin environment feature vectors), where e_i^k represents the feature vector of cabin environment, t_i represent the score under k, $z_{i,k}^{j,l}$represents the co-occurrence value in the case where e_i^k and e_j^l correspond.

Therefore, the feature vector of the training cabin environment under RIM can be expressed by Eq. (1).

$$\min_{\tilde{e}_*,\hat{e}_*,b_*} \hat{J}_t = \sum^T_{t_i^k,t_j^l \in T, k\neq l, z_{ti,k}^{tj,l}>0} \left((\tilde{e}_i^k)^T \hat{e}_j^l + b_i + b_j - \log z_{ti,k}^{tj,l}\right)^2 \tag{1}$$

Similarly, RIM can also be used to train operator eigenvectors. The corresponding objective function is shown in Eq. (2).

$$\min_{\tilde{r}_*,\hat{r}_*,b_*} \hat{J}_t = \sum^T_{u_i^k,u_j^l \in T, k\neq l, \hat{z}_{i,k}^{j,l}>0} \left((\tilde{r}_i^k)^T \hat{r}_j^l + \hat{b}_i + \hat{b}_j - \log \hat{z}_{ti,k}^{tj,l}\right)^2 \tag{2}$$

In Eq. (2), both $\tilde{r}_i^k$ and $\hat{r}_i^k$ are operator feature vectors of operator u_i under score k. In order to learn the RIM eigenvectors of the operator and the cabin environment, they are adopted to minimize the objective functions Eq. (3) and Eq. (4), respectively.

The partial derivative of the objective function to the operator eigenvector or cabin environment eigenvector is shown in Eq. (3).

$$\frac{\partial J_t}{\partial \tilde{e}_i} = 2\varphi \tilde{e}_i, \frac{\partial J_t}{\partial \tilde{e}_j} = 2\varphi \tilde{e}_j, \frac{\partial J_t}{\partial b_i} = 2\varphi, \frac{\partial J_t}{\partial b_j} = 2\varphi,$$

$$\frac{\partial J_u}{\partial \tilde{r}_j} = 2\tau \tilde{r}_i, \frac{\partial J_u}{\partial \tilde{r}_j} = 2\tau \tilde{r}_j, \frac{\partial J_u}{\partial b_i} = 2\tau, \frac{\partial J_u}{\partial b_j} = 2\tau. \tag{3}$$

in,

$$\varphi = \tilde{e}_i^T \hat{e}_j + b_i + b_j - \log y_i^j,$$

$$\tau = \tilde{r}_i^T \hat{e}_j + \hat{b}_i + \hat{b}_j - \log \hat{y}_i^j \tag{4}$$

Similarly, the objective functions Eq. (5) and Eq. (6) for RIM have the following,

$$\frac{\partial \hat{J}_t}{\partial \tilde{e}_i^k} = 2\hat{\varphi} \tilde{e}_i^k, \frac{\partial \hat{J}_t}{\partial \tilde{e}_j^l} = 2\hat{\varphi} \tilde{e}_j^l, \frac{\partial \hat{J}_t}{\partial b_i} = 2\hat{\varphi}, \frac{\partial \hat{J}_t}{\partial b_j} = 2\hat{\varphi},$$

$$\frac{\partial \hat{J}_u}{\partial \tilde{r}_i^k} = 2\hat{\tau}\tilde{r}_i^k, \frac{\partial \hat{J}_u}{\partial \tilde{r}_j^l} = 2\hat{\tau}\tilde{r}_j^l, \frac{\partial \hat{J}_u}{\partial \hat{b}_i} = 2\hat{\tau}, \frac{\partial \hat{J}_u}{\partial \hat{b}_j} = 2\hat{\tau}. \tag{5}$$

in,

$$\hat{\varphi} = \left(\tilde{e}_i^k\right)^T \hat{e}_j^l + b_i + b_j - \log z_{i,k}^{j,l},$$

$$\hat{\tau} = \left(\tilde{r}_i^k\right)^T \hat{r}_j^l + \hat{b}_i + \hat{b}_j - \log \hat{z}_{i,k}^{j,l} \tag{6}$$

Finally, as shown in Eq. (7), the feature vectors to be learned are updated.

$$\tilde{e}_i \leftarrow \tilde{e}_i - \omega \frac{\partial J_t}{\partial \tilde{e}_i}, \hat{e}_i \leftarrow \hat{e}_i - \omega \frac{\partial J_t}{\partial \hat{e}_i}, \tilde{e}_i^k \leftarrow \tilde{e}_i^k - \omega \frac{\partial \hat{J}_t}{\partial \tilde{e}_i^k},$$

$$\hat{e}_j^l \leftarrow \hat{e}_j^l - \omega \frac{\partial \hat{J}_t}{\partial \hat{e}_j^l}, \tilde{r}_i \leftarrow \tilde{r}_i - \omega \frac{\partial J_u}{\partial \tilde{r}_i}, \hat{r}_j \leftarrow \hat{r}_j - \omega \frac{\partial J_u}{\partial \hat{r}_j},$$

$$\tilde{r}_i^k \leftarrow \tilde{r}_i^k - \omega \frac{\partial \hat{J}_u}{\partial \hat{r}_i^k}, \hat{r}_j^l \leftarrow \hat{r}_j^l - \omega \frac{\partial \hat{J}_u}{\partial \hat{r}_j^l} \tag{7}$$

where ω is the learning rate.

2.3 Predictive Neural Network

In this paper, the eigenvectors of the operator and the cabin environment obtained through the feature learning model reveal the co-occurrence characteristics of both, but these eigenvectors cannot directly obtain the results of final score prediction. Therefore, an additional component is required to estimate the operator's rating of the cabin environment. Due to the artificial neural network can effectively extract features, simulate complex objective functions, and fuse input features from multiple angles, the neural networks are an ideal model for rating prediction [19-20].

The goal of scoring prediction is to input a real-number predicted value according to the characteristics of the given operator and the cabin environment. This predicted value represents the estimation of the score given by the operator to the cabin environment. The neural network is used to directly input the pre-obtained characteristics of the operator and the RIM in the cabin environment into a feed-forward neural network to obtain the predicted value. In order to further improve the prediction ability of the model, a new perspective based on the historical records of the operator and the cabin environment can be introduced. Both the perspectives of the operator and the cabin environment of the current perspective and the historical perspective can be recorded, that is, through RIM feature input and after updating the features are inputs to form a multi-view neural network, which can be divided into a multi-view feature extraction stage and an integrated prediction stage.

In order to obtain the prediction of the cabin environment t_j given to the operator u_i, in the feature extraction stage, two kinds of feature inputs under the current viewing angle and the historical viewing angle are required. For the current perspective, you need to input the feature vectors corresponding to u_i and t_j ; for the historical perspective, you need to input the representation of the historical features obtained from the cabin environment that has been evaluated historically by the operator u_i, and the operator that has been evaluated by the cabin environment t_j, a representation of the historical characteristics of the cabin environment. Among of them, the network inputs the RIM features of the operator and the cabin environment from the current perspective and the historical perspective respectively.

Therefore, the composite connection vector $\alpha_u^t = [\beta_u(u_i), \beta_t(t_j), \gamma_u(u_i), \gamma_t(t_j)]$ from both perspectives, the remaining score prediction part of the neural network can be expressed as Eq. (8).

$$d_{i,j} = f_\sigma(\alpha_u^t). \tag{8}$$

In Eq. (8), $d_{i,j}$ is the predicted score of the operator and the cabin environment, f_σ is the feedforward neural network, σ is the parameter that the network needs to learn, and the activation function g used in f_σ is defined as $g(x) = max(x, 0)$.

The feature extraction part of different perspectives is the main component of the neural network. The following is the extraction process:

2.3.1 Feature extraction of current view

Since there may be specific r_i^k or e_j^k that cannot be obtained through the training set, especially the zero vector is used to represent the operator u_i and the cabin environment $t_j$in these special cases. Given K different scoring categories, there will be K RIM eigenvectors representing different ratings, the calculation process is shown in Eq. (9).

$$v_i(u_i) = [r_i^1, r_i^2, \ldots, r_i^k], \mu_j(t_j) = [e_i^1, e_i^2, \ldots, e_j^k] \tag{9}$$

where $v_i(u_i)$ and $\mu_j(t_j)$ are the unique integrated RIM eigenvectors for u_i and t_j, respectively.

Since the RIM feature vectors with different scores actually exist in the same space, in order to effectively extract features from v_i and μ_j, the extraction equation in this mode is shown in 10.

$$\begin{aligned} v_i^k(u_i) &= g(\widehat{W}^r v_i(u_i)[(k-1) \times l_r : k \times l_r]), \\ \mu_j^k(t_j) &= g(\widehat{W}^e \mu_j(t_j)[(k-1) \times l_e : k \times l_e]). \end{aligned} \tag{10}$$

Among them, l_r and l_e represent the dimension of RIM vector r_i^k and e_j^k respectively, $v_i(u_i)[(k-1) \times l_r : k \times l_r]$ is $v_i(u_i)$from the $(k-1) \times l$ element to the $k \times l$th element, $\widehat{W}^r$ and $\widehat{W}^e$ are the shared parameter matrices of the operator and the cabin environment, respectively.

2.3.2 Historical perspective feature extraction

In order to effectively process the historical information, it is first necessary to perform further feature extraction on the operator's evaluated cabin environment set or feature vectors corresponding to the operator's evaluated cabin environment set. Based on the RIM feature model, it is assumed that T_i^k represents the set of cabin environments with score K given by operator u_i, and U_j^kdenotes the set of operators who give score K to cabin environment t_j. $y^k(u_i)$ and $\hat{y}^k(t_j)$ are the historical features corresponding to u_i and $t_j$under the score K, respectively. The corresponding formulas of $y^k(u_i)$and $\hat{y}^k(t_j)$ are shown in Eq. (11).

$$y^k(u_i) = \frac{\sum_{t_j \in T_i^k} e_i^k}{|T_i^k|}, \hat{y}^k(t_j) = \frac{\sum_{u_i \in U_j^k} r_j^k}{|U_j^k|}. \tag{11}$$

The operator and the cabin environment combine the historical features $s(u_i)$and $\hat{s}(t_j)$under the score in K as shown in Eq. (12).

$$s(u_i) = \left[s^1(u_i),, s^2(u_i)\ldots, s^k(u_i), \hat{s}(t_j) = \hat{s}^1(t_j), \hat{s}^2(t_j), \ldots, \hat{s}^k(t_j)\right]. \tag{12}$$

2.3.3 Integrated prediction stage

In the integrated prediction stage, the features obtained in the previous step are fused into a unified feature vector through an integration layer to represent the interaction characteristics of the operator and the cabin environment. Finally, the fused feature is used as input, and the prediction score of the operator $u_i$and the cabin environment t_j is output through a situation network.

The error function used to train the predictive neural network is the mean square error function (MSE), as shown in Eq. (13).

$$min\frac{1}{|A|}\sum_{u_i,t_j\in A}(f_n(u_i,t_j) - r_i^j)^2 \tag{13}$$

In Eq. (8), f_n represents the multi-view network, and n is the parameter that needs to be learned. A is the training set, and each sample in the training set is an operator u_i, cabin environment t_j and the corresponding score r_i^j.

The neural network is trained by stochastic gradient descent (SGD), and the evaluation result of the network on the verification set is used as the condition for ending the training early. If performance does not improve within a few epochs on the validation set, then training ends.

3. Results

According to the research method of this paper, after interacting with the operator and the cabin environment, the operator is mainly scored from the following dimensions: vision, hearing, touch, smell, perception, and the overall comfort of the cabin. In terms of scoring, it is mainly scored from the following dimensions: lighting environment, air quality, temperature, noise environment, and cabin layout.

First, search for 500 groups of military cabins with high comfort ratings and input their various parameters into the neural network, and input the scores at the same time to determine the scoring standard. Next, input the parameters of the military cabin design plan into the neural network, so as to obtain the predicted score and recommend the optimal design scheme. Second, the optimal design obtained by the artificial intelligence-based recommendation model in this paper was tested in various simulation scenarios and achieved satisfactory results. The model can effectively predict and evaluate the cabin design scheme, recommend the optimal cabin design scheme, shorten the time of design, and reduce the cost of design.

4. Conclusions

The application of artificial intelligence in the design of military cabins is expected to provide engineers with efficient solutions to design the cabin environment and ease the complexity of military cabin design. The artificial intelligence-based recommendation model proposed in this paper provides a novel and effective approach for designing military cabins. The model considers various factors that affect the cabin environment and provides an optimized solution for cabin design. Future work includes developing an integrated system that allows real-time adjustments to the cabin environment based on recommendations provided by artificial intelligence-based models. The accuracy of the models can be improved by adding data sources and improving machine learning algorithms.

The AI-based recommendation model proposed in this paper has great potential in the field of military cabin design. Applying artificial intelligence to military cabin design promises to revolutionize the way engineers design cabin environments, and the model offers a cost-effective way to optimize cabin environments and improve crew safety and health. By using an artificial intelligence-based system, engineers can reduce the time and resources required to design cabins, resulting in shorter delivery times and lower costs.

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