The Scheme Design of Wearable Sensor for Exercise Habits Based on Random Game

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***Abstract*—The development of random game theory has enabled wearable sensors to obtain actuator evolution in sports exercise, thus the design of user exercise habits during the exercise process has begun to be studied. Conventional devices only focus on automatic adjustment of sports design, with slight shortcomings in personalization. To address this issue, this study added an anchor node localization device to the adaptive search hybrid learning algorithm and analyzed the exercise goals of athletes. At the same time, a semi definite programming method was installed in wearable sensors to achieve the goal of paying attention to the physical condition of athletes. To verify the performance of the fusion device, this study conducted experiments on the Physical dataset and compared it with three models such as Harris Eagle Optimization. The accuracy rates of designing exercise habits schemes for the four devices were 97.4%, 96.5%, 94.7%, and 91.2%, respectively, indicating that the model has the strongest stability. Under the same running time, the energy loss of this model was 0.11kW * h, which performs the best among the four models. When the athletes are different in age, the F1 values of the four devices are 5.9, 4.5, 4.2 and 3.6 respectively. The results indicate that the proposed fusion model has strong robustness and is suitable for designing exercise habit schemes in the evolution of sports exercise actuators.**

Keywords*—Random game; adaptive search hybrid learning algorithm; wearable sensors; physical exercise; evolution of actuators; exercise habits; anchor node positioning; semi definite programming method

I. INTRODUCTION

The continuous advancement of technology enables wearable sensors to collect the biological information of athletes, providing them with guidance on exercise plans [1-2]. In recent years, sports exercise actuators have gradually integrated electronic technology, providing a more personalized exercise experience. With the increasing emphasis on physical exercise, wearable sensors, as an emerging technology, have been widely used in the field of physical exercise. It can monitor individual exercise data in real-time, such as heart rate and sleep quality, providing users with scientific health guidance and personalized exercise plans. In addition, some sports exercise actuators are also equipped with computer systems, which can help users to better grasp the exercise effect [3]. Conventional sensors are limited to real-time monitoring of body status, and designing the optimal exercise habit plan based on user characteristics still poses challenges [4]. And this method is only suitable for users who exercise in specific areas. For enthusiasts of special terrains, these methods are prone to over generalization during runtime. To expand the search domain of wearable sensors for physical exercise, this study pioneered the construction of a Stochastic Games (SG) model to simulate the decision-making process of physical exercise personnel in different contexts.

A wearable sensor was designed based on the Adaptive Hybrid Learning of Search (AHLS) algorithm to monitor athletes. To accurately locate it, this study designed Anchor Node Positioning (ANP) technology in wearable sensors and generated a fusion model (AHLSG-PEA). The main content of the study can be divided into six sections. Section I mainly analyze and summarize the application of the current AHLS algorithm. Related works is given in Section II. Section III introduces AHLS and SG into SG and sensors. Section IV conducts simulation experiments on the Physical dataset. Section V delves into results and discussion. And finally, Section VI concludes the paper. The theoretical significance of this study lies in providing a device for designing exercise plans, aimed at helping users achieve a better exercise experience and thus maintain physical health. The theoretical significance of this study lies in providing a device for designing exercise plans, aimed at helping users achieve a better exercise experience and thus maintain physical health.

II. RELATED WORKS

In the field of scheme design algorithms, research is widely distributed internationally. Nagal et al. designed a system using a hybrid whale grey wolf optimization algorithm. Their algorithm utilized whale parameters to control and balance the randomness of the strategy. For noise in computer signals, they used a controlled search space for filtering. The performance experiment of the algorithm was conducted through signal-to-noise ratio and its average value relationship was evaluated. This algorithm had better strategy planning ability compared to other technologies [5]. Zhou et al. conducted research on the knapsack problem and considered knapsack preferences to extend quadratic multiple knapsacks. They proposed a hybrid evolutionary search algorithm for backpack strategy analysis and generated new offspring solutions based on the crossover operator of the backpack. The experimental analysis of this algorithm utilized adaptive feasible taboo search to improve the offspring solution. This method could accelerate the generation of candidate solutions and streamline their evaluation to propose the best solution [6].

The methods of scheme design are becoming increasingly widespread, and the design of exercise habits is also becoming popular. Meng et al. considered that the sparrow search algorithm is a metaheuristic optimization method, so they applied it to handle multimodal optimization problems. They first introduced chaotic mapping in their research, while also using adversarial learning methods to increase the diversity of strategies. To verify its effectiveness, they conducted a large number of experiments in the test suite and demonstrated that this method outperforms conventional optimization algorithms in terms of performance [7]. Suresh et al. believed that the recursive whale algorithm has decision-making ability, so they proposed an optimization method for smart grid utilization by reducing production costs through real-time scheduling. The search behavior of this algorithm was experimentally conducted on a work platform through taboo search. The decision capability analysis of this method indicated that the proposed method has less time for scheme design [8]. Yuan led his research group to study the scheme design ability of the population, and adjusted the coordinate system based on the covariance matrix to move the population towards a more favorable direction. To enhance the suggestion ability of covariance, they learned evolutionary algorithms to improve search efficiency. Compared with other algorithms, experiments have shown that this algorithm is a high-quality algorithm [9]. Rajendran et al. found that manual methods have drawbacks in radiation, so they conducted research on computer-aided diagnosis and believed that the most important step is feature selection. Considering that recent algorithms are prone to falling into local optima, they combined grasshoppers with crows to verify that the proposed multi-layer perceptron has strong feature selection ability. This simulation experiment was conducted on MATLAB and compared with many similar algorithms, and its accuracy, sensitivity, and specificity have been proven to be superior to other algorithms [10]. Zhang et al. believed that the evolution of wind speed prediction actuators has a significant impact on decision analysis in the wind power industry, so a hybrid prediction model was developed. In this model, the secondary decomposition technique used wavelet transform. This technology has the ability to adaptively process data, so that the characteristic components of the signal would also be extracted. The experimental verification was conducted using real-life wind turbines and compared with the same prediction algorithm, proving that the model has the smallest statistical error and the strongest adaptability in performance [11].

Numerous experts and scholars have found that research on the application of KM and Long Short Term Memory (LSTM) is very popular, but research on large-scale datasets is still scarce. This study innovatively links the two and holds significant importance in dataset processing.

III. An ANP Solution for SG in Exercise Habits

SG involves the uncertainty faced by participants in exercise decision-making, making it difficult to accurately predict determined exercise habits. To assess the evolving exercise habits of physical exercise actuators (PEA), this study combines the AHLS algorithm and uses ANP to select appropriate exercise habits based on the current search state during user exercise.

A. Wearable Sensor Combining AHLS Algorithm with SG

The characteristic of SG is that the actions of physical exercise personnel are influenced by random factors, and therefore cannot be determined through simple optimal strategies. So researchers need to weigh different choices based on probability and adopt appropriate strategies to deal with uncertainty. In practical applications, the analysis of SG requires the use of probability theory methods to determine the optimal strategy and final outcome for each athlete, as shown in Formula (1).

$$\begin{cases} F(X) = d\left(X * \left(\Pr_1 - \Pr_0\right)\right)/dt \\ \Pr_0 = X^T * X * X_0 * k \end{cases} \tag{1}$$

In Formula (1), $\Pr_1, \Pr_0$ represents the probability of the athlete generating random ideas. X is the final choice of the sports personnel at the time of the event. The time experienced in this process is denoted as X^T, and the cooperative effect they have is represented by X_0. k is the environmental parameter of the process. In order to help athletes adapt to this trend, this study added the AHLS algorithm to SG, as shown in Formula (2) [12].

$$AH_x = \sum_{i=1}^{I} \sum_{j=1}^{J} A_i^j * H_{ij} \tag{2}$$

In Formula (2) above, the expected result of SG combined with the AHLS algorithm (AHLSG) is represented by H_{ij}. A_i^j represents the process network loss during algorithm operation. In the AHLSG algorithm, AHLS uses domain knowledge and empirical rules to guide the search process and quickly find the expected solution of the algorithm [13]. The advantage of the AHLSG algorithm is that it can flexibly select search strategies based on the characteristics of the problem. During the operation of the AHLSG algorithm, the popular domain will also be determined, as shown in Formula (3).

$$d\Delta Ca / di = C_i * \left(\sum_{i=1}^{I} \left(Ar_i - Ar_0\right)\right) - \sum_{t=1}^{T} \sum_{z=1}^{Z} a_t a_z \tag{3}$$

In Formula (3), the running parameters of the AHLSG algorithm are represented by Ar_i, Ar_0. The running intervals of the algorithm at the current time and the initial time are denoted as a_t, a_z. C_i represents the expected value of the AHLSG algorithm for the research input. The operation of this algorithm requires a large amount of motion habit features to establish machine learning models, which will impose a burden on the computational cost of the algorithm [14]. To reduce the running time of the algorithm, a model was established for this study, as shown in Fig. 1.

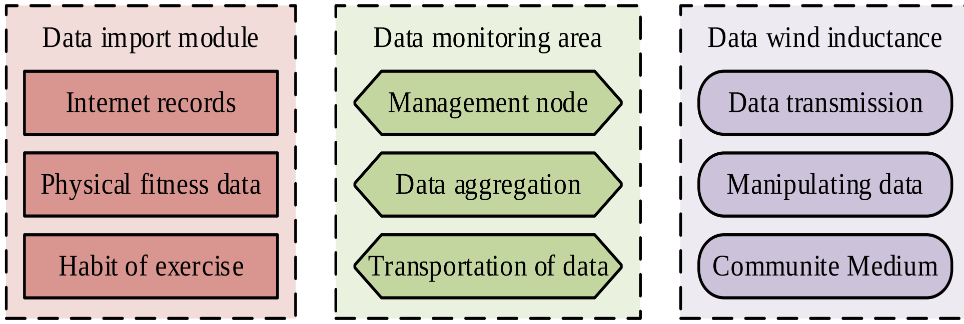


Fig. 1. Algorithm flow chart combining AHLS and SG.

In Fig. 1, in the motion data processing of the algorithm, the AHLS algorithm represents the motion contour as a level set, which has good robustness. SG smooths the data to remove noise from motion data. The characteristic of SG is high computational efficiency, but its performance is highly dependent on the quality of training data. So this study introduces ANP in SG, combining anchor nodes with the exercise habits of athletes, as shown in Formula (4) below.

$$\begin{cases} An_1 = \left(An_0 - 1\right)^2 * \left(0.5 * \Delta Ca + 0.25\right) \\ No_2 = \left(\partial No_1\right) * \left(0.1 * N_2 + 0.75 * N_1\right) \end{cases} \tag{4}$$

In Formula (4) above, the anchor position of the personnel is represented by An_1. An_0 is the duration of movement at that location. N_2 and N_1 represent two different methods of motion at different times, and the stability of these two methods is denoted as No_1. No_2 represents the positioning of the research hypothesis. This study applies ANP to exercise habit judgment and obtains spatial location information of athletes. Based on the results of this data analysis, this study was able to determine the suitable exercise habits as anchor nodes, as shown in Fig. 2.

Fig. 2 is a motion habit determination method based on anchor nodes. When athletes tend to exercise during a specific time period, the machine will choose that time period as the anchor node. Then, based on the selected anchor node, the motion target of the mover on it is set [15].

Based on the exercise habits of the athletes, the machine provides them with personalized exercise advice to help them better achieve movement on anchor nodes. The comparison method between athletes is Formula (5).

$$Co_1 * \int_{-\pi}^{+\pi} \alpha_1 * \beta_1 d\alpha d\beta = Co_2 \int_{-\pi}^{+\pi} \alpha_2 * \beta_2 d\alpha d\beta \tag{5}$$

In equation (5), the exercise method of the athlete before and after the suggestion is denoted as α_1, α_2. β_1, β_2 represents the difficulty coefficient when they are implemented. Both are highly sensitive to the quality of the environment they are in, so variables caused by environmental factors are represented by Co_1, Co_2. The limitations of this method are the dynamics and persistence of motion on anchor nodes. To address this issue, this study combines ANP and AHLSG algorithms in sensors to design a novel motion habit scheme, as shown in Fig. 3.

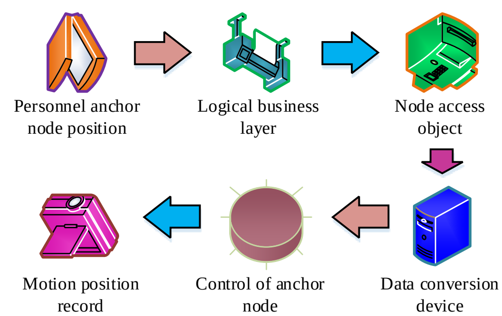


Fig. 2. Determine the exercise habit process diagram as the anchor node.

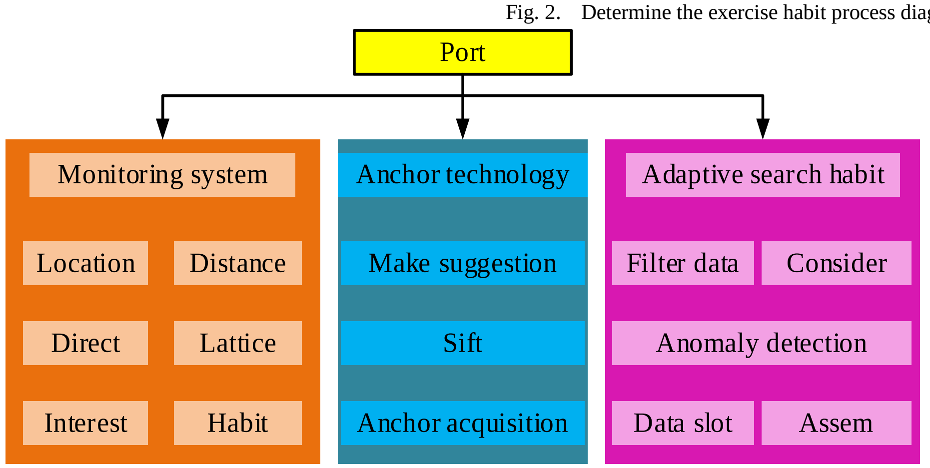


Fig. 3. Exercise habit design scheme combining anchor node positioning and AHLSG algorithm.

In Fig. 3, this method can help researchers judge exercise habits and choose exercise paths based on the behavioral patterns of the athletes. ANP technology provides location information for athletes, and this method can evaluate the quality of movement of athletes. This study combines this method with motion sensor technology, as shown in Formula (6) [16]. This method can not only classify the user's movement behavior, but also analyze the user's posture change information. By evaluating whether the athlete's movements are correct, their exercise methods, such as running and cycling, can be analyzed.

$$\begin{cases} de_1 = de_k / \mu_k \\ \mu_k = \left[\left(de - de_1 \right) / \left(de_k - de_1 \right) \right]^{0.5} \end{cases} \tag{6}$$

In Formula (6), the initial signal of the sensor is denoted as de_1, and its total electrical energy intensity during working time is represented by de. de_k, μ_k represents the peak intensity and energy loss of the sensor signal at the current time. This sensor records motion data through devices such as smart wristbands, which can monitor the movement behavior of athletes in real time and provide real-time motion guidance. This study first helps athletes correct bad habits based on their location information, and then makes actual adjustments to the exercise plan based on the exercise time and weather. The degree of adjustment is Formula (7) below.

$$Ha(x) = -de_k * \int_0^1 (\chi_x + \delta_x) d\chi + \mu_k * \int_0^1 (\chi_x + \delta_x) d\delta \tag{7}$$

In Formula (7), $Ha(x)$ is the current habit of the athlete. χ_x represents the time interval of exercise. The weather conditions during exercise are represented by δ_x. This study combines wearable sensors with the AHLSG algorithm to obtain the movement trajectories of athletes under different exercise habits, thereby conducting in-depth research on individual exercise habits. As the strategies of athletes change, this method can reveal their decision-making process in exercise habits, providing scientific basis for developing personalized exercise habit improvement plans. This method has the ability to improve individual health levels when applied in the field of sports exercise actuator evolution.

B. Design of AHLSG -based Sensors in the Evolution of Sports Exercise Actuators

PEA evolution refers to the process of improving PEA performance in terms of design and performance. The function of this mechanical device is to assist in basic physical exercise movements [17]. Conventional actuators only have simple adjustment functions and lack personalized adjustments. To improve this point, this study will design sensors based on AHLSG in PEA, combined with the method shown in Formula (8).

$$Act_a = \left\{ Sen_a * \left\| Sen_b - Act_b \right\|_a^b , Sen \in Act \right\} \tag{8}$$

In Formula (8), Sen_a, Act_a represents the initial data of the sensor and actuator. The elements they combine in the two are represented by Sen_b, Act_b. Sen, Act represents the units to which two devices belong. Through this method, sensors and actuators generate a personalized sports exercise program design device (AHLSG-PEA). This study first used sensors to monitor key indicators of exercise personnel, and analyzed the data collected by the sensors, as shown in Fig. 4 [18].

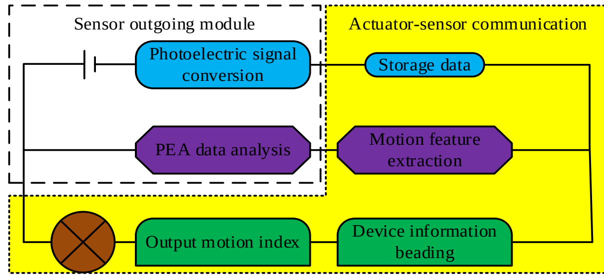


Fig. 4. Workflow of personalized physical exercise program design device AHLSG-PEA.

Fig. 4 shows the process of designing exercise habits for the AHLSG-PEA device. The data of the sensor module is first scheduled using the AHLSG algorithm, and then a motion data model based on motion personnel is established. PEA plays a clustering role in it [19]. The physiological indicators of personnel include blood flow rate and heart rate information. Finally, this study used the proposed algorithm for real-time data analysis, as shown in Formula (9).

$$\begin{cases} \phi_a = \left[\varepsilon_a * \left(Sen_a / Act_a \right) + \gamma_a \right]^{0.5} \\ \varphi_a = \left(1 - \varepsilon_b \right) * \left(\Delta\Omega \right)^2 \end{cases} \tag{9}$$

In Formula (9), the physiological indicators of the exerciser are denoted as ε_a. ε_b is the psychological indicator of the same personnel. The coefficient of conversion between the two is represented by γ_a. $\Delta\Omega$ represents the clustering center of the PEA work process. The analyzed data can be used to construct suitable exercise plans based on the goals of physical exercise. The plan includes action sequences, action specifications, and exercise intensity, and real-time processing of feedback information based on algorithms. Due to the unique characteristics of athletes, it is necessary to automatically adjust the parameters of the exercise model in order to achieve a wide range of exercise effects. The adjustment method follows Formula (10).

$$\eta_1 = arc \min_{\eta_1 \in \eta} \int \int_{\eta_1}^{\eta} \sqrt{\eta_1 - \left(\eta_0 + \phi_a \forall \varphi_a \right)^2} \tag{10}$$

In Formula (10), η_1 represents the current planning method for exercise habits. η_0 is the optimal design for studying the preset. The AHLSG-PEA device has an evolutionary optimization effect on PEA, while setting a fitness function in the device to continuously optimize the parameters of the actuator to improve its adaptability [20]. The real-time motion data information of athletes can be fed back to the AHLSG-PEA instrument in real time and provide real-time suggestions. This method can help users adjust their strength and rhythm to achieve better exercise results, as shown in Fig. 5.

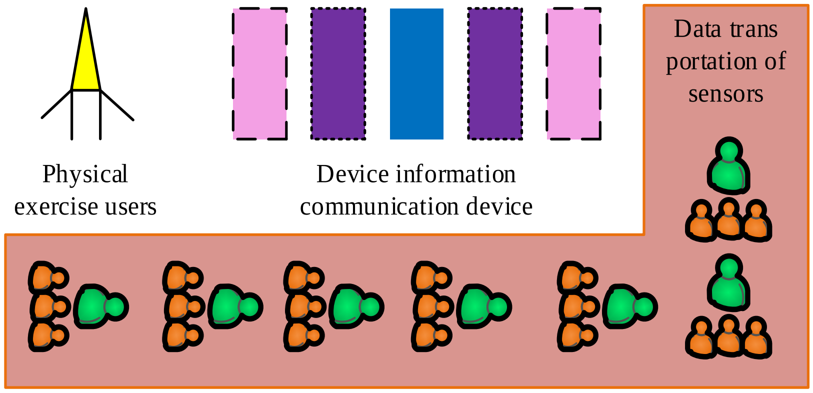


Fig. 5. Real-time feedback process diagram of motion data of AHLSG-PEA instrument.

In Fig. 5, sensor technology and real-time feedback mechanism are combined in AHLSG-PEA. This method can track the human body's motion trajectory in real-time based on the motion contour. In sports actuators, this study will use the AHLSG algorithm to provide real-time exercise recommendations. Then, the raw data collected by the sensor is filtered and denoised to improve the stability of the proposed results. In order to update the motion contour model in real-time, this study incorporated the semi definite programming method into the AHLSG-PEA device. The main purpose of this method is to optimize the motion parameters, and the optimization method is Formula (11).

$$Po_i*\left(-1+\sum_{i=1}^{I}\coprod_{j=1}^{J}Se_i/Se_j\right)=1+\sum_{i=1}^{I}\coprod_{j=1}^{J}\left(Se_i+Se_j\right) \quad (11)$$

In Formula (11), the weather conditions during exercise are denoted as Po_i. Se_i, Se_j represents the position and mood parameters of athletes in the semi definite programming method. In the optimized AHLSG-PEA device, this study uses rules for information exchange, enabling information to spread across the network. In this device, this propagation method is referred to as rule propagation. The rule propagation model is used to help instruments understand information, where the propagation path is a key factor in the propagation process, represented by Formula (12).

$$Sp(e)=Sp_1+Sp(e-1)/10*\left[\lg\left(e_0/e\right)\right] \quad (12)$$

In Formula (12), $Sp(e)$ represents the dissemination method of the exercise participants at the current location. The propagation path of the previous athlete is represented by $Sp(e-1)$. Sp_1 represents the perfect path preset by the AHLSG-PEA device. The communication barriers between them are denoted as $\lg\left(e_0/e\right)$. This method can predict the behavioral information of athletes. By simulating their propagation process, this study can evaluate the impact of different strategies on exercise habits and guide the development of exercise methods. In addition, the rule propagation method can also set the optimal motion node, as shown in Fig. 6.

In Fig. 6, when setting the optimal motion node, this study first collects data related to the motion node, including information on population density and distribution of motion facilities. Then, based on the physical exercise goals of the athletes, evaluation indicators are determined to measure the suitability of each potential exercise node. Based on the collected data and determined evaluation indicators, the suitability of each potential motion node is evaluated, as shown in Formula (13). This formula can be used to analyze the evolving motion habits of actuators.

$$Pot_m=\left(Pot_1/Pot_n+1\right)\Theta Sp(e)-\left(Pot_0/Pot_n+1\right) \quad (13)$$

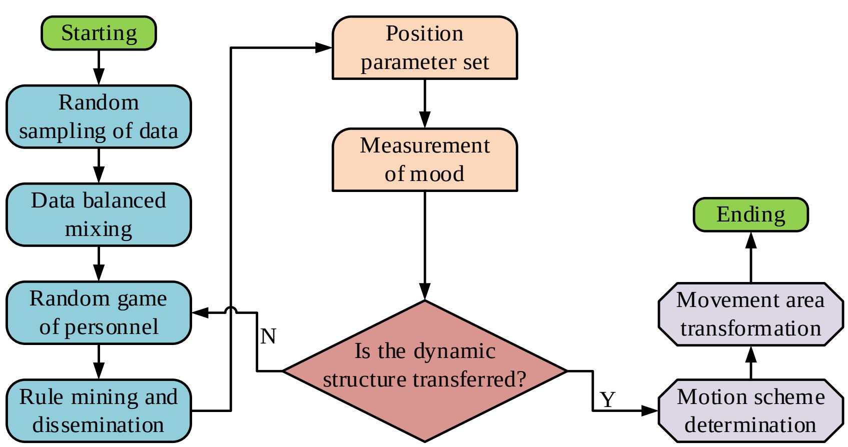


Fig. 6. Process diagram of method for setting optimal motion node through rule propagation.

In Formula (13), Pot_1, Pot_0 represents the motion nodes in different regions. Pot_m represents the motion node selected as the latent state. The optimal state of this point is represented by Pot_n. After obtaining potential motion nodes, suitability scores were assigned to each node. Based on the evaluation score, the best motion node will be selected. Finally, this study suggests that there may be noise issues in real-world nodes, so adjustments are made based on feedback information, as shown in Formula (14).

$$Fee(n) = \sum_{i=1}^{I} \left[(Fee_i - Fee_1) * (Fee_1 - Fee_m)^2 \right]^{1/2} / \sum_{m=1}^{M} Pot_m \quad (14)$$

In Formula (14), the first feedback information of the real node is denoted as Fee_1, and there are a total of Fee_i feedbacks. Their mean is represented by Fee_m. $Fee(n)$ represents the output information of the model in the ideal state, in order to achieve the preset constraints of the research. This method can maximize the exercise effect of athletes, and then transform the problem of designing exercise habits into evolutionary optimization of algorithms to improve the adaptability of AHLSG-PEA devices, as shown in Formula (15).

$$\mu_{eq} = \nu(T) - \theta(T) * \vartheta_{eq} * \varpi \lg(\sigma / \sigma_0) \quad (15)$$

In Formula (15), the performance of the AHLSG algorithm caused by time is denoted as $\nu(T)$. The noise changes are represented by $\theta(T)$. ϑ_{eq} represents the external environmental factor of the AHLSG-PEA device. ϖ is a variable caused by the device's own factors. σ / σ_0 represents the loss coefficient during signal propagation. Through the above scheme design, the AHLSG-PEA device can achieve personalized exercise plans in the evolution of PEA, thereby improving the safety of exercise. Meanwhile, through continuous evolutionary optimization and real-time feedback, the performance of the actuator can be gradually improved, providing a better exercise experience for exercise users. Stochastic game theory is used to analyze the decision-making rules between physical exercisers, and provides the corresponding strategy updating direction for adaptive search hybrid learning algorithm. At the same time, the adaptive search hybrid learning algorithm constantly optimizes the search process and finds the optimal solution of exercise habits in a more efficient way. The combination of these two methods plays an active role in solving the problem of optimal strategy selection in actuator evolution. Anchor node positioning technology can be used to determine the target position. This paper studies the combination of anchor node positioning technology and adaptive search hybrid learning algorithm to make the random game process better adapt to the needs of sports habits in different environments. And by studying the proposed optimization process, the accuracy of positioning is improved.

IV. Example Analysis of the Fusion Algorithm AHLSG-PEA in the Design of Exercise Habit Schemes

This study conducted experiments on the Physical dataset and compared it with three other models to verify the superiority of the AHLSG-PEA device. This dataset contains a total of 857 exercise habits from different regions, including almost all ages of athletes.

A. Performance Verification of Wearable Sensors for SG

This study was divided into two groups in a 6:12 ratio for the rational utilization of limited data in the Physics dataset, and algorithm learning and experimental verification were conducted on them respectively. Table I shows the equipment screening and parameters used in the experiment.

This study conducted performance validation of the AHLSG-PEA device after setting parameters according to Table I, and compared it with the AHLS algorithm, Harris Hawks Optimization (HHO) algorithm, and Convolutional Neural Network (CNN). The experimental results are shown in Fig. 7.

TABLE I. Equipment Selection and Parameter Determination in Performance Verification Experiment of DWKM-LSTMIA Algorithm

Equipment selection	Parameter determination
Master client	Intel Yeon E8-2079
Language	Easy Chinese
Memory of graphics card	2T*8
Operating system	Windows 7X
Age range of athletes	5-80
Athletes' sports terrain	Plains, mountains, hills and lakes
Sensor wearing habit	Shoulder, hand, neck and ankle
Time range of movement	Morning, afternoon, evening, early morning
Algorithm working time	15:22:59
Data set	Physic
Execution method	Matlab R2147h

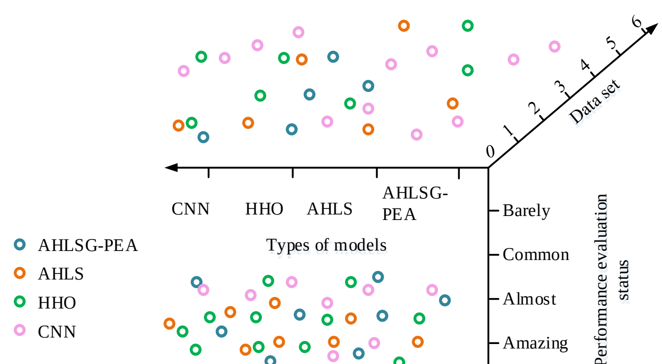


Fig. 7. Image of performance verification experiment results of AHLSG-PEA equipment.

Fig. 7 shows a comparison of the design capabilities of four different systems for exercise habits. As the model runtime increases, the performance ratings of all four algorithms continue to rise, and the AHLSG-PEA device consistently performs the best. At the same time, the debugging levels of AHLSG-PEA, AHLS, HHO, and CNN equipment were 5.8, 4.6, 4.1, and 3.7, respectively. This indicates that the performance of AHLSG-PEA devices is optimal when the operating environment is the same. To verify the robustness of the AHLSG-PEA model, this study conducted experiments on different exercise times and locations, and the experimental results are shown in Fig. 8.

In Fig. 8 (a), when the model is located in the same region, the performance of all four models shows an upward trend as the running time increases. The working characteristic value of AHLSG-PEA equipment is the highest, at 28. The control conditions in Fig. 8 (b) are the same running time but different exercise locations. In Fig. 8 (b), as the exercise location of the participants becomes increasingly difficult, the calculation accuracy of all four models shows a decreasing trend. The highest accuracy values of AHLSG-PEA, AHLS, HHO, and CNN devices are located at 63, with values of 94.5%, 92.7%, 84.1%, and 82.6%, respectively. This indicates that the AHLSG-PEA device can accurately design the exercise habits of athletes. However, the above experiments can only demonstrate the internal performance of the equipment, and experimental verification is also required for changes in the conditions of the athletes themselves.

B. *Experimental Analysis of AHLSG-PEA Equipment under the Background of PEA Evolution*

To conduct experiments on the performance of AHLSG-PEA equipment in the evolution of PEA, this study focused on the different habits of athletes, as shown in Fig. 9.

Fig. 9 shows the AHLSG-PEA performance experiment under different habits of athletes. In Fig. 9 (a), as the number of participants in the exercise gradually increases, the accuracy of scheme design for all four systems shows an upward trend. Among them, the proposed system has the highest calculation accuracy of 99.7%. In Fig. 9 (b), the scheme design accuracy of AHLSG-PEA, AHLS, HHO, and CNN devices are 97.4%, 96.5%, 94.7%, and 91.2%, respectively. This indicates that AHLSG-PEA can adapt to different time habits in exercise program design. The results of the experiment on athletes from different sports locations are shown in Fig. 10.

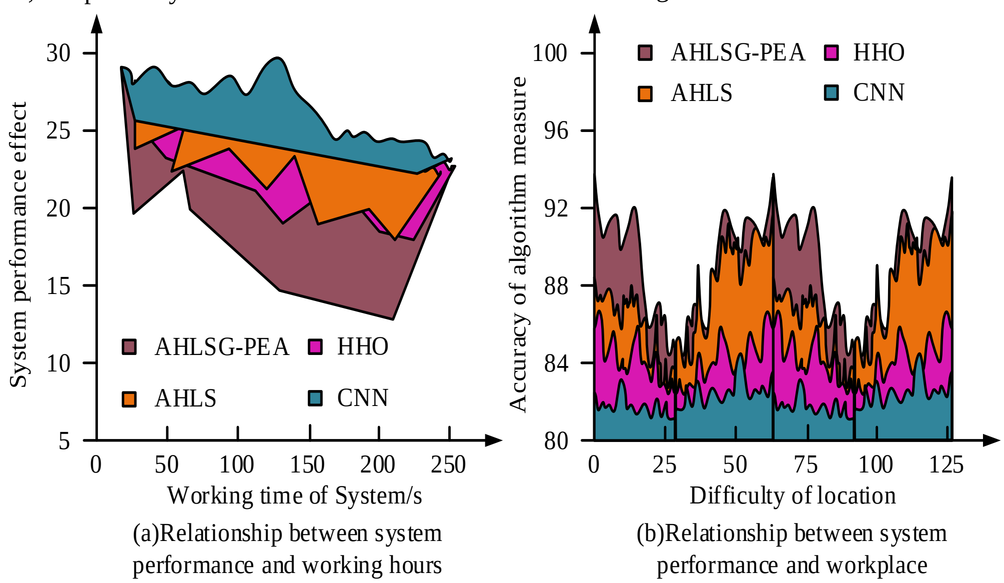


Fig. 8. Experimental results of robustness of AHLSG-PEA model.

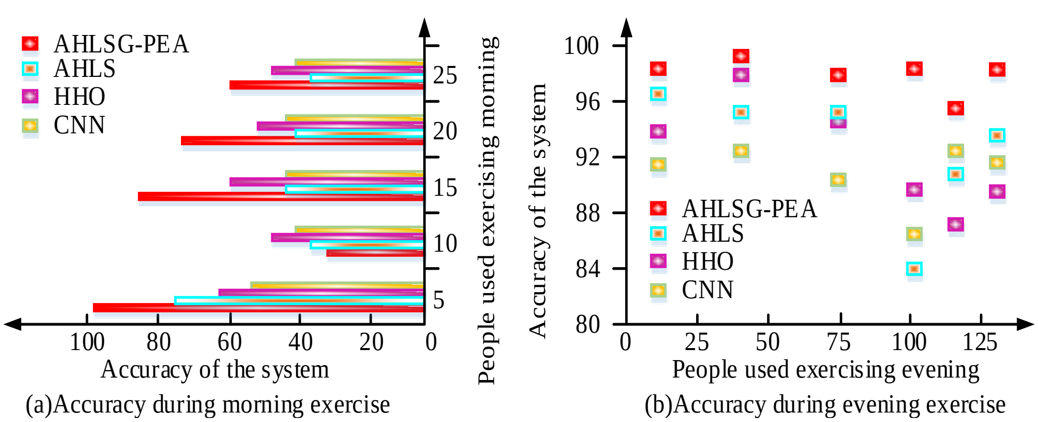
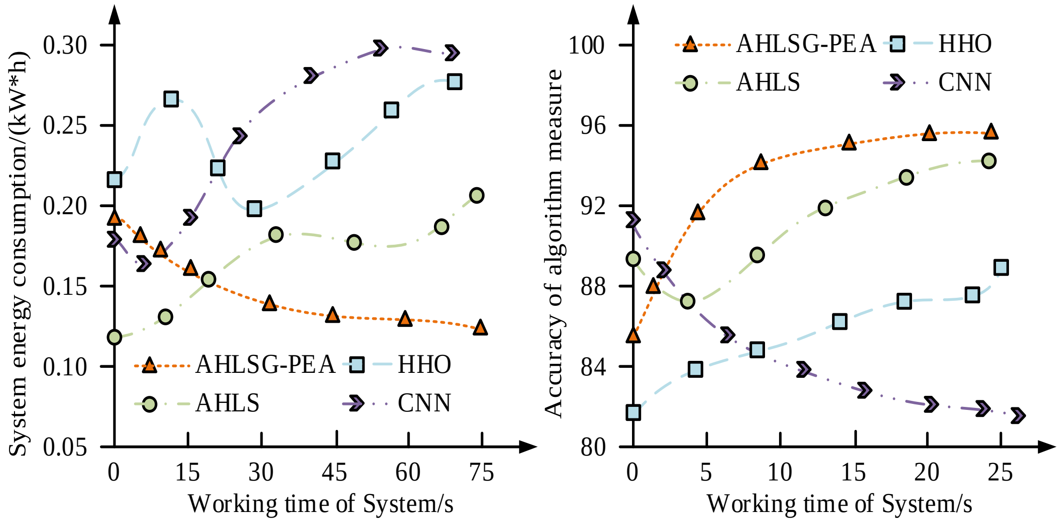


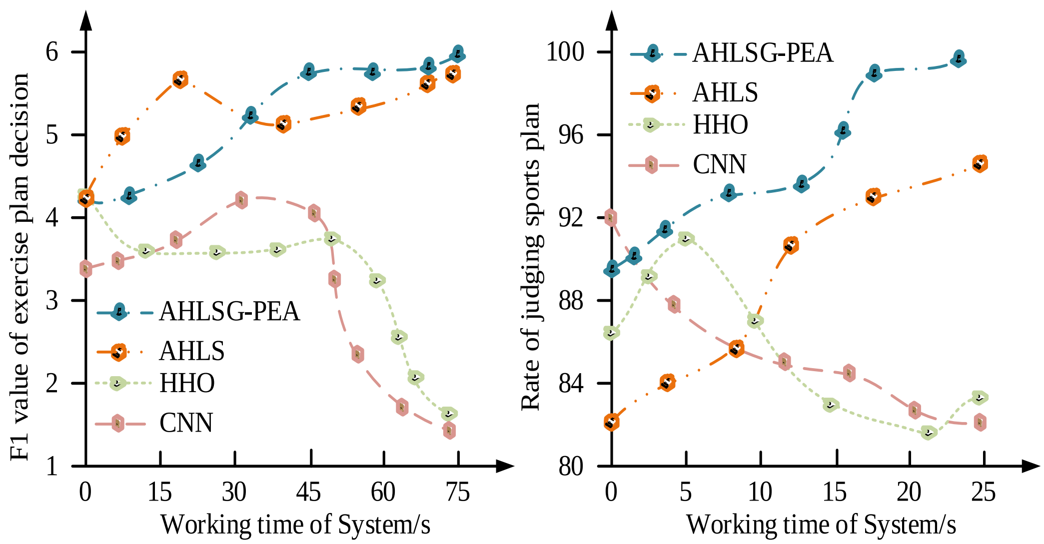
Fig. 9. Performance experiment of AHLSG-PEA equipment in different habits of athletes.



(a)Performance experiment of athletes in plain terrain

(b)Performance experiment of athletes in mountainous terrain

Fig. 10. Scheme design of AHLSG-PEA equipment when athletes move in different places.



(a) Experiment on judging sports plan of young athletes

(b) Experiment on judging exercise plan of middle-aged athletes

Fig. 11. Experimental results of extensive verification of AHLSG-PEA model.

In Fig. 10 (a), the energy losses of AHLSG-PEA, AHLS, HHO, and CNN equipment in plain terrain are 0.11, 0.19, 0.24, and 0.28 kW * h, respectively. This indicates that the proposed model has the highest economic benefits. In Fig. 10 (b), the accuracy of determining the motion habits of the four models in hilly terrain is directly proportional to the running time of the models, and the research model always has the highest accuracy, at 95.8%. This indicates that the AHLSG-PEA model has the best judgment performance. To verify the universality of the model, the results of experiments conducted on users of different ages are shown in Fig. 11.

Fig. 11 shows the extensive validation of the AHLSG-PEA device for young and middle-aged athletes participating in sports activities. In Fig. 11 (a), the F1 value of the AHLSG-PEA device is the highest, at 5.9, indicating that the model has the strongest stability in experiments with young people. In Fig. 11 (b), the accuracy of AHLSG-PEA, AHLS, HHO, and CNN instruments are 99.8%, 97.2%, 94.1%, and 92.5%, respectively. Therefore, the AHLSG-PEA device has the best performance in designing exercise habits in the evolution of PEA, which is suitable for optimizing the user's exercise experience.

V. Results and Discussion

Random game theory is a mathematical model used to analyze the game process of sports. Adaptive search hybrid learning algorithm combines adaptive search and hybrid learning process, while anchor node positioning is used to locate the target position. In this study, these three methods are integrated to construct a wearable sensor under the background of the evolution of physical exercise actuators, and its application ability in the design of exercise habits is discussed.

The research experiment is divided into two parts, including the test of internal performance and the proof of robustness, effectiveness and universality. The experiment of this model is carried out in the Physic data set and compared with the other four methods. When the running time of the model increases, the performance scores of the four algorithms are rising, and the AHLSG-PEA device always performs best, which shows that the performance of the device is the best. The highest accuracy of AHLSG-PEA device is 94.5%, and its performance is the best among the four devices, which shows that it can accurately predict the exercise habits of athletes.

When the four kinds of equipment are faced with the choice of exercise habits at different times, the accuracy of their scheme design is 97.4%, 96.5%, 94.7% and 91.2% respectively, which shows that the AHLSG-PEA model proposed in this study has good adaptability to different times. The energy loss of AHLSG-PEA instrument is 0.11 kW*h for detecting the exercise habits of athletes in different environments. Compared with AHLS, HHO and CNN, this figure can show the highest economic benefit and the best performance in energy loss. When faced with the detection of exercise habits of people of different ages, the proposed device has the highest F1 value, which shows its strong robustness.

To sum up, the integration technology of random game theory, adaptive search hybrid learning algorithm and anchor node positioning (AHLSG-PEA) is robust, effective and extensive in the design of exercise habit scheme. The experimental results show that the AHLSG-PEA instrument proposed in this study can effectively design the exercise habits of physical exercisers on wearable sensors, and is suitable for being widely used in sports navigation systems. When athletes use non-contact sensors, the research method has certain limitations. With the continuous development of artificial intelligence technology, this integration method will also be more widely studied.

VI. Conclusion

With the evolution of PEA, the recommendation of exercise habits is gradually becoming more personalized. This study added SG technology to the AHLS algorithm and designed it simultaneously with ANP in the sensor, generating the AHLSG-PEA model. To verify its practicality and universality, this study conducted experiments on the Physical dataset and compared the results with AHLS, HHO, and CNN devices. In the internal performance test, the debugging levels of the four instruments were 5.8, 4.6, 4.1, and 3.7, respectively, indicating that the AHLSG-PEA equipment has the best performance. The highest accuracy values of AHLSG-PEA, AHLS, HHO, and CNN devices were 94.5%, 92.7%, 84.1%, and 82.6%, respectively, indicating that AHLSG-PEA devices can accurately predict the exercise habits of athletes. The accuracy rates of scheme design for AHLSG-PEA, AHLS, HHO, and CNN devices were 97.4%, 96.5%, 94.7%, and 91.2%, respectively, for model performance at different times, indicating that the model has good adaptability to different times. For different terrains of athletes, the energy consumption of the four instruments was 0.11, 0.19, 0.24, and 0.28 kW*h, respectively, indicating that the proposed model has the highest economic benefits. When the age of athletes was different, the F1 values of AHLSG-PEA, AHLS, HHO, and CNN devices were 5.9, 4.5, 4.2, and 3.6, respectively, indicating that the AHLSG-PEA device has robustness in the age experiment of athletes. The experimental data showed that the device proposed in this study can effectively cope with internal parameters and external environment, thereby providing users with effective motion plans. However, this study only focuses on wearable sensors, and this method has certain limitations when non-contact sensors are used by athletes. This is because the total amount of data in the dataset is limited. As the number of volunteers increases, this limitation will gradually improve in future research.

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