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Optimized design of a virtual simulation system for motion anatomy incorporating deep forest algorithms

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SUMMARY: *This study proposes an optimization architecture based on the deep forest algorithm to address the problems of low accuracy, slow response and poor adaptability of the traditional motion anatomy virtual simulation system. The algorithm learns multi-level features from motion anatomy data through the cascade forest mechanism, which effectively improves the accuracy of motion pattern recognition and the ability of anatomical structure association analysis. The system adopts end-to-end design and contains four core modules. The multi-source data acquisition module integrates inertial sensors, optical motion capture, and other types of signals. The feature extraction module utilizes multi-granularity scanning technology to generate multi-scale feature vectors. The deep forest processing module realizes layer-by-layer feature abstraction through cascade structure. The simulation and rendering module finally outputs highly realistic 3D visualization results. Experiments show that the optimized system significantly outperforms the traditional method in key indexes such as motion recognition accuracy, joint angle prediction, muscle activation pattern classification, etc., and at the same time, it also performs better in terms of real-time performance and system robustness.*

KEYWORDS: *deep forest algorithm; motion anatomy; virtual simulation; feature learning; real-time performance*

1 Introduction

The essence of sports is physical activity under the supply of energy, therefore, exploring the laws of sports must be based on understanding the morphological structure of the body. Sports anatomy is based on the study of the normal morphology and structure of the human body, focusing on analyzing the role of exercise on the morphology and structure of the human body, growth and development, and combining the requirements of technical movements and anatomical knowledge to guide the teaching of sports [1-4]. However, conventional anatomy teaching resources and modes are difficult to effectively express the joints and muscles of the movement mode and movement state, unable to meet the requirements of sports anatomy teaching on the intuitive and practical, and the rehabilitation training of sports injuries also need to understand the principle of joints and muscles of the movement. For this reason, the virtual simulation system of sports anatomy based on virtual simulation technology is gradually developed and applied.

Virtual simulation technology is relying on the Internet, multimedia, virtual reality, human-computer interaction and other technologies continue to develop, combined with simulation technology and virtual reality and other technologies evolved more powerful technology [5-7].

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Based on virtual simulation technology, the virtual simulation system of sports anatomy is based on the executive system, guarantee system and regulation system of the human body function system, integrating the structure of each part of the executive system, muscle position, muscle starting and stopping points, name, function and other knowledge contents [8-10]. In the actual teaching application, the teacher can explain the basic knowledge through the operation function of the system, but also mark on the 3D animation, with 3D model animation, active classroom atmosphere, which greatly improves the students' interest in learning [11-13]; the system can also better assist the students to understand the movement characteristics of the various joints, muscles, and the built-in exercise module provides a carrier for testing the students' understanding of the degree of knowledge [14-16]. In addition, in order to improve the intelligence of the system, the deep forest algorithm used for classification, regression and other problems can be integrated, which can equip the system with the ability to understand, evaluate and adapt to the personalized human movement state, and play an important role in sports training, rehabilitation, immersive education and other aspects [17, 18].

In this paper, a kind of deep forest model based on cascade forest is constructed to mine deep-level motion features in motion anatomical information, and use these features to improve the classification accuracy of motion states and the judgment of anatomical relationships corresponding to human motion parts. This method is directly from the original input data, and after the data collection unit, feature processing unit, deep forest unit, and visualization and display unit successfully uses the system for the effective improvement of the correctness of the motion recognition, the estimation of the joint angles, and the discrimination of the EMG patterns.

2 Design of a virtual simulation system for motion anatomy incorporating deep forest algorithms

2.1 Simulation system design

Sports anatomy is to explore the structure of the human movement system and its functional relationship, and reveal its regularity of knowledge of a discipline, for the design and development of virtual simulation system is of great significance, because it is a set of human movement biomechanics of the basic scientific basis. The human motion system includes bone, muscle and nerve control and so on many parts, under certain conditions, they constitute a complete biomechanical device, and the activities of the joints are in line with the dynamics of the rigid body, the changes in the spatial attitude of the rigid body can be expressed by the chi-square transformation matrix. There is a complex nonlinear correspondence between the angle change and the muscle contraction force, and the Hill muscle model provides a mathematical expression for this relationship, the force F generated by the muscle is related to the contraction velocity v and the muscle length l as:

$$F(v,l) = F_{\max} \cdot f_l(l) \cdot f_v(v) \cdot a(t) \tag{1}$$

where $F_{\max}$ represents the maximum isometric contraction force, $f_l(l)$ represents the length-tension relation function, $f_v(v)$ is the velocity-tension relation function, and $a(t)$ represents the neural activation level.

VR technology is the core technical basis of simulation, involving computer graphics, human-computer interface and immersive display and other technical sub-disciplines, three-dimensional graphic drawing is to achieve realistic visual presentation with the help of geometric models and light illumination models in the virtual environment, ray tracing tracks the movement of light in space, and the rendering equation describes the process of light interacting with surfaces in the scene:

$$L_o(p,\omega_o) = L_e(p,\omega_o) + \int_{\Omega_i} f_r(p,\omega_i,\omega_o) L_i(p,\omega_i)(\omega_i \cdot n) d\omega_i \tag{2}$$

where L_o is the luminance of outgoing radiation, L_e is the luminance of spontaneous light radiation, f_r is the bi-directional reflection distribution function, L_i is the luminance of incident radiation, ω_i and ω_o denote the direction of incoming and outgoing radiation, respectively, and n is the surface normal vector.

The real-time rendering algorithm ensures the interactive response performance of the system, the optimization strategies such as hierarchical detail model and cone culling effectively reduce the computational complexity, and the spatial localization tracking technology realizes the accurate mapping between the user's action and the virtual environment, which provides a solid technical foundation for the construction of a high-fidelity sports anatomy simulation environment.

The simulation system design theory provides system engineering methodology support for the virtual simulation system architecture of sports anatomy, the discrete event simulation theory abstracts the complex system as a sequence of state-changing events, the event scheduling mechanism realizes the accurate simulation of the system dynamic behavior, and the state transfer process is expressed as:

$$S(t+\Delta t) = f(S(t), E(t), P) \tag{3}$$

where $S(t)$ represents the state of the system at the moment t, $E(t)$ is the set of events, P is the system parameter, and f is the state transfer function.

The hierarchical modeling method decomposes the complex motion anatomical process into multiple interrelated subsystems, with each subsystem assuming a specific functional module, the interface standardization realizes the data exchange and collaborative work between the modules, the system verification and validation theory guarantees the credibility of the simulation results, and the statistical test method evaluates the consistency between the simulation outputs and the real system, and the validation process covers the model validation, data validation, and result validation at three levels. The validation process covers three levels: model validation, data validation and result validation. The deep forest algorithm is based on the decision tree integration and deep learning fusion framework to build an innovative integrated learning method, cascading forest structure to achieve deep feature learning, each layer contains multiple random forests, and the information transfer between the layers realizes the gradual abstraction and refinement process of features. Multi-granularity scanning mechanism converts the original input data into multi-scale feature representation, the length of n sequence data using a sliding window with a window size of w to generate $n-w+1$ sub-sequences, each sub-sequence is processed by the random forest to obtain the category probability vector, the output of the l th layer of the cascade forest is expressed as:

$$H^{(l)} = \left[H^{(l-1)}, F_1^{(l)}(H^{(l-1)}), F_2^{(l)}(H^{(l-1)}), \cdots, F_k^{(l)}(H^{(l-1)}) \right] \tag{4}$$

where $H^{(l-1)}$ is the output of the previous layer, and $F_i^{(l)}$ is the mapping function of the i th forest in the l th layer.

The deep forest algorithm has the ability to adjust the complexity of the adaptive model, and the cross-validation mechanism automatically determines the optimal number of layers, which avoids the overfitting problem of the traditional deep learning, and at the same time maintains the advantage of the interpretability of the decision tree model, which provides an effective theoretical tool to deal with the complex nonlinear relationship of the sports anatomical data.

2.2 Deep Forest Algorithm

Deep forest jumps out of the traditional deep learning model and establishes a new type of deep learning method without using any backpropagation technique with random forests as the basic unit, and implements a layer-by-layer feature extraction function similar to that of DNN on this model: the deep forest consists of a number of cascade forests, a cascade forest contains a number of random forests, and there exists an information flow between different cascade forests, i.e., the samples input to the k+1th cascade forest are the samples that have already been processed in the kth cascade forest. However, the inherent interpretability and nonparametric advantages of the decision tree model are maintained.

Where multi-granularity scanning is used to map the input data to subsets at different scales, the cascade forest performs recursive deep abstraction analysis. Compared with traditional deep neural network models, the algorithm uses cross-checking to automatically determine the optimal number of cascade forest layers, which avoids the tedious process of performing hyperparametric optimization. The algorithm is trained level by level, and each level of forest is obtained by continuing training on the basis of the previous level, and if the next level of forest is small for the test accuracy enhancement, new forests will not be added; because the decision tree has the characteristics of independent training, the algorithm can accelerate the speed of massive data model training by using the current mainstream multi-core processors, which will provide a technical way for the real-time application to land.

The multi-granularity scanning mechanism of the algorithm utilizes the sliding window technique to extract local feature information from multiple scale dimensions. For an input sequence of length L, the system adopts a sliding window strategy with a window size of w_i to generate $(L - w_i + 1)$ subsequence segments, and each subsequence outputs the corresponding category probability vectors after Random Forest processing, and the splicing of multi-window scale feature vectors forms an enhanced feature representation. The splicing operation of multi-window scale feature vectors forms an enhanced feature representation. Each layer of the cascade forest receives the output of the previous layer and the spliced vectors of the original features as input data, and the output expression of the l th layer is:

$$F(T) = \sum_{i=1}^{n} \alpha_i \cdot f_i(T) \tag{5}$$

where T denotes the input feature vector, $f_i(T)$ is the output of the i th random forest, α_i is the corresponding weight coefficient, and n is the number of forests contained in the layer.

A combination strategy of completely random tree and extreme random tree is implemented within each random forest, where the completely random tree performs splitting operation by randomly selecting features at each node, and the extreme random tree randomly determines the splitting threshold on randomly selected features, and this diversity strategy significantly enhances the generalization performance of the integrated model. Due to the use of a validation set for monitoring, after the number of cascade layers is increased to a certain level, if the accuracy is not significantly improved in the newly added layers, the training process is terminated and the final result is obtained directly to avoid overfitting.

Since the deep forest method has outstanding advantages in big data and the type of data involved in the virtual simulation system of sports anatomy happens to be big data, it provides a possibility to realize the combination of the deep forest algorithm and the virtual simulation technology of sports anatomy. At the same time, the human motion capture data belongs to the large amount of big data, and contains angle information, electromyographic signals and spatial position information and other index data. The above signals have complex temporal and spatial correlations. Due to the non-parametric characteristics of the algorithm itself, it can automatically mine the distribution law in the data without presetting any information about the data distribution, and it has better stability for the data containing noise, and it will make segmentation of outliers in the process of generating the decision tree; moreover, the integrated approach can reduce the impact of outliers on the performance of the final model. Multi-granularity scanning is able to obtain the change state of the motion pattern from different time scales, short time granularity to extract the detail information in the motion, and long time granularity to obtain the motion trend and cycle information. The cascade forest structure gradually abstracts the high-level semantic information of the motion through a hierarchical feature learning process, where the bottom forest focuses on the monitoring of changes in the basic motion parameters, and the top forest is responsible for learning the complex coordination patterns of the motion in correlation with anatomical structures.

2.3 Design of the architecture of the virtual simulation system for sports anatomy

The experimental platform for virtual simulation of motion anatomy adopts a layered architecture model, and the overall framework is shown in Fig. 1. It combines the deep forest algorithm with traditional virtual simulation by building a comprehensive platform integrating data acquisition, data analysis, virtual simulation and visualization. The main technical features are that the deep forest method is fully utilized in the overall process, and the learning process from low-level sensing information directly to high-level semantic representation is completed in end-to-end mode, and the basic software development principles are followed, and there are unified input and output specifications to support the interactive operation between different modules. The requirements of scalability and easy maintenance of the system are effectively ensured.

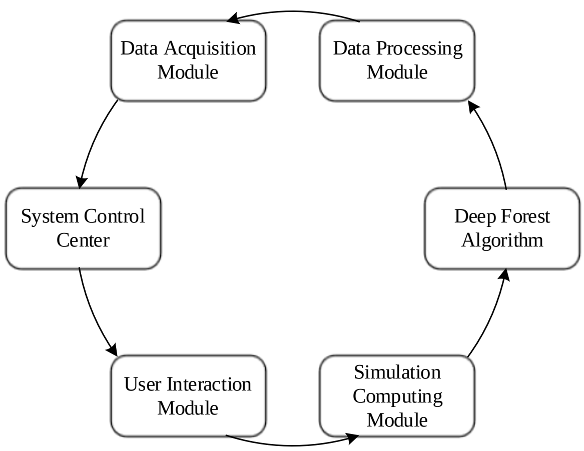

Figure 1: Architecture of Virtual simulation System for sports anatomy

The acquisition system is responsible for real-time acquisition of data from various types of sensors, including IMU, Vicon motion capture instrument, sEMG, and plantar pressure measurement system, and time-stamping these data to ensure that the data from various types of sensors have a unified time reference. Among them, the inertial guidance module can give high data of joint angular velocity and joint angular acceleration with an accuracy of 1 KHz. cursor locator can obtain high accuracy to locate the position of the object in three-dimensional space with an accuracy of less than millimeter level. The surface EMG signal can record the electrical signal activity of muscles in real time, and multiple electrodes are used to record the target muscles in parallel in the experiment. Meanwhile, the change of pressure value measured by plantar pressure measurement is one of the important bases for analyzing the walking style and stability. The internal data checking function of the system can effectively judge the collected data and eliminate the invalid data; at the same time, the system will calibrate the sensors from time to time to eliminate the errors brought by external interference and changes in the characteristics of the sensors themselves, so as to ensure the normal operation of the system.

In the data analysis layer, in order to realize the intelligence of the system, this paper designs a deep forest-based data analysis flowchart, which is used to automatically transform the collected signals into semantic information describing the motion, and complete the work of data cleaning, noise reduction, and normalization, etc. In this process, adaptive filters are used to denoise the signals, eliminate unnecessary background noise and clutter, and ensure the quality and stability of the input data.

The feature extraction sub-module utilizes a multi-granularity scanning technique to extract multi-scale feature representations from the time series data, and generates feature vectors using a sliding window strategy with a window size of $w_1, w_2, \cdots, w_k$ for motion sequences of length N:

$$F = \left[f_1^{(w_1)}, f_2^{(w_2)}, \cdots, f_k^{(w_k)} \right] \tag{6}$$

where $f_i^{(w_i)}$ denotes the extracted feature vector when the window size is w_i. The deep forest processing sub-module implements feature hierarchical learning using the cascade forest architecture, and the l th level output is computed by the following equation:

$$H^{(l)} = Concat\left(H^{(l-1)}, RF_1^{(l)}(H^{(l-1)}), RF_2^{(l)}(H^{(l-1)})\right) \tag{7}$$

where $RF_i^{(l)}$ denotes the mapping function of the l th layer of the i th random forest, and $Concat$ is the vector splicing operation. The simulation module is based on the advanced physics engine to construct a high-fidelity human kinematic model, and integrates the core algorithms of rigid-body dynamics, constraint solving and collision detection.

The human skeletal system is modeled with a multi-rigid-body chain structure to deal with the joint constraints, and the system dynamics equations are expressed as:

$$M(q)\ddot{q} + C(q, \dot{q}) + G(q) = Q + J^T \lambda \tag{8}$$

where M is the mass matrix, C is the Coriolis and centrifugal force term, G is the gravity term, Q is the generalized force, J is the constrained Jacobi matrix, and λ is the Lagrange multiplier.

For muscle modeling, the Hill muscle model is used to simulate the muscle contraction behavior and input the neural activation information to obtain the moment value of the muscle action. The simulation part and the data analysis part communicate with the above model to obtain the motion prediction information of the deep forest algorithm as the motivation of the simulation, and obtain the result of the simulation and send it back to the algorithm module for updating. The human-computer interface layer has a user-friendly visual 3D graphical interface and an advanced graphics rendering engine to provide an excellent visual experience, as well as physically-based light rendering functions, including dynamic shadows, specular reflection, and light transmission to provide an immersive experience for the user. The human body model uses a fine mesh for real-time deformation and texture mapping; bone-based human motion simulation produces smooth and natural movement; and the human body can be manipulated via mouse buttons, touch screen, microphone, and camera to meet the needs of different users.

The integrated VR and AR technologies can provide users with an immersive virtual reality experience, allowing users to wear helmets and learn about motion interaction in a virtual environment; the integrated real-time visualization module can present the results obtained by the deep forest classifier in the form of images, heat maps, and stereoscopic images, which facilitates the users' understanding of the complex knowledge of motion anatomy. Configurable: Users can personalize the content of the interface according to their own field of expertise, making the operation of the whole system more humanized and professional; Manager: acts as a manager in each sub-system, mainly used to coordinate the task execution of each sub-system, resource allocation, and contingency measures in the event of accidents, so as to enable the system to work normally and smoothly.

3 Data-processing model design

For motion anatomical data, a mapping relationship from the raw sensor acquisition data to the final motion state information expression should be established before analyzing it using deep forests. The deep forest-based human motion data analysis framework proposed in this study utilizes the ability of deep forest to extract features layer by layer from the bottom up to solve complex action recognition tasks. First, multi-source heterogeneous sensor signal inputs are processed for adaptive signal conditioning. In order to solve the problem of bias accumulation in the inertial measurement unit, a method of online correction of systematic errors occurring in the process of inertial measurement unit using Kalman filtering method is proposed here. The spatial missing points of the optical streak type motion capture system are supplemented by the interpolation method. The EMG signals were band-pass filtered from 20 to 500 Hz to remove the grid-frequency components contained therein; then full-wave rectified and low-pass filtered to obtain the surface EMG activity amplitude information. Data synchronization is achieved by hardware timestamps and software interpolation algorithms to achieve sub-millisecond precision alignment, and outlier detection is based on the outlier identification method of statistical distribution to automatically handle abnormal samples.

The feature extraction phase utilizes the multi-granularity scanning mechanism of deep forest to obtain multi-scale feature representations from the time series. For a motion sequence $X = \{x_1, x_2, \cdots, x_T\}$ with a length of T, the window size set $W = \{w_1, w_2, \cdots, w_k\}$ Performs a multi-granularity scan, generating $(T - w_i + 1)$ subsequence fragments for each window w_i. The process of feature vector construction can be expressed as follows:

$$F_{mg} = Concat\left(\bigcup_{i=1}^{k} F^{(w_i)}\right) \tag{9}$$

where $F^{(w_i)}$ represents the set of feature vectors when the window size is w_i, and $Concat$ performs the vector splicing operation.

The time domain includes mean, variance, skewness, cragness, etc.; the frequency domain is to obtain the power spectral density map of the collected time series by fast Fourier transform; the time-frequency domain is to analyze the frequency characteristics of the signal localized by using wavelets; the change information of the joint points mainly refers to the information of angular velocity and angular acceleration embedded in the angle of the joints; the numerical differentiation is to solving; and muscle activity patterns are applied to extract the main synergistic patterns by principal component analysis. Spatial features are computed to characterize the motion geometry by calculating the relative position and attitude relationships between joints.

The model is trained using a deep forest cascade learning strategy to abstract the features layer by layer, and each layer contains multiple random forests to enhance the diversity of the model. The output of the l th layer of the cascade forest is computed as:

$$H^{(l)} = \left[H^{(l-1)}, RF_1^{(l)}\left(H^{(l-1)}\right), RF_2^{(l)}\left(H^{(l-1)}\right), \cdots, RF_m^{(l)}\left(H^{(l-1)}\right) \right] \tag{10}$$

where $H^{(l-1)}$ is the output feature of the previous layer, $RF_j^{(l)}$ denotes the l th layer of the j th random forest mapping function, and m is the number of forests per layer.

Cross-validation splits into a training set, a validation set, and a test set; the training set is resampled using a self-help method to create a training subset in a random forest; and the decision tree is created with a split decided at each node based on a randomly selected subset of features. The number of decision trees in the forest is found by a grid search to find the optimal setting, and the depth of the model is automatically determined by performance monitoring on the validation set, and the number of layers is not continued when the boost from adding a layer is less than a certain threshold.

Model optimization includes hyper-parameter auto-tuning, model compression and inference acceleration to improve computational speed. The hyperparameter auto-tuning technique based on Bayesian optimization is used to find the best hyperparameter combinations, which adopts a probabilistic model that establishes the relationship between the hyperparameters and the objective function to drive the hyperparameter optimization; the pruning method is used to cut down the low-impact decision tree to simplify the model, and to reduce the complexity of the model based on the assurance of the model's accuracy. Knowledge distillation transfers knowledge from complex deep forests to simple models for lightweight deployment; utilizes a combination of model-parallelism and data-parallelism for inference acceleration; uses caching techniques to cache the results of completed computational processes to reduce redundant computations; and introduces adaptive batch processing techniques to automatically determine batch sizes. Online learning ensures that the model can be continuously updated with personalized and adaptive parameters as new samples arrive; the incremental learning process eliminates the need to retrain the overall model; model integration techniques are used to integrate the results of multiple deep forests in order to achieve higher accuracy and greater stability, and to compute the appropriate weighting values according to the different situations.

4 System implementation and experimental analysis

4.1 System implementation

The software part of this system is mainly written by VisualStudio2022 integrated development platform to write the framework, and use Python3.9 programming to realize the depth forest algorithm, use OpenGL4.6 for animation rendering and display function, and GPU computing to improve the performance and realize the real-time three-dimensional dynamic picture. Use Qt6.2 framework to design and develop the multi-platform user interface in the program, and use signal slot technology to achieve low-coupling transfer between modules when interacting information between different functional modules; save a large amount of motion data in PostgreSQL14 database and use Redis database to improve the efficiency of reading commonly used data.

The machine learning library of scikit-learn is extended to realize deep forest, and the core code part is accelerated by using Cython; RESTful interfaces are used for information interaction between various microservices; and unified development and deployment are completed in Docker containers; Project management and automated builds, tests, and releases with Git and Jenkins. Ensure program quality and system stability. The data acquisition module integrates a unified interface layer for all kinds of sensor devices, and the device abstraction layer shields the differences between the hardware of various vendors. IMU data is read through the serial port at a frequency of 1000 Hz, and the data of each sensor is synchronized using a timestamp based on the starting byte of the frame; the 3D position information obtained after synchronization is sent to the Vicon software, where the loss and tracking failure are set. The EMG data are converted to voltage signals by a signal conditioning circuit, and the EMG signals of each muscle group are acquired simultaneously, and finally the effects of noise and AC power interference are eliminated by a low-pass filter.

The performance indicators of each module of the system are shown in Figure 2, the performance test results show that the system in the standard configuration environment, the CPU utilization rate of the system integration is 53.6%, the delayed response of data processing is controlled within 30ms to meet the needs of real-time applications, the system integration test verifies that the modules work together to stabilize the reliability of the system integration test. Stress test verifies the stability of the system under high concurrent access and large data processing scenarios, and memory leakage detection tool ensures the reliability of long-time operation. The compatibility test covers the mainstream operating system and hardware platforms to ensure that the system is widely applicable. Security testing identifies potential security risks through penetration testing and code auditing, and data encryption and access control mechanisms protect user privacy and security. The monitoring system tracks the operation status in real time, log analysis tools assist in troubleshooting and performance optimization, and automated operation and maintenance scripts simplify the system maintenance and management process.

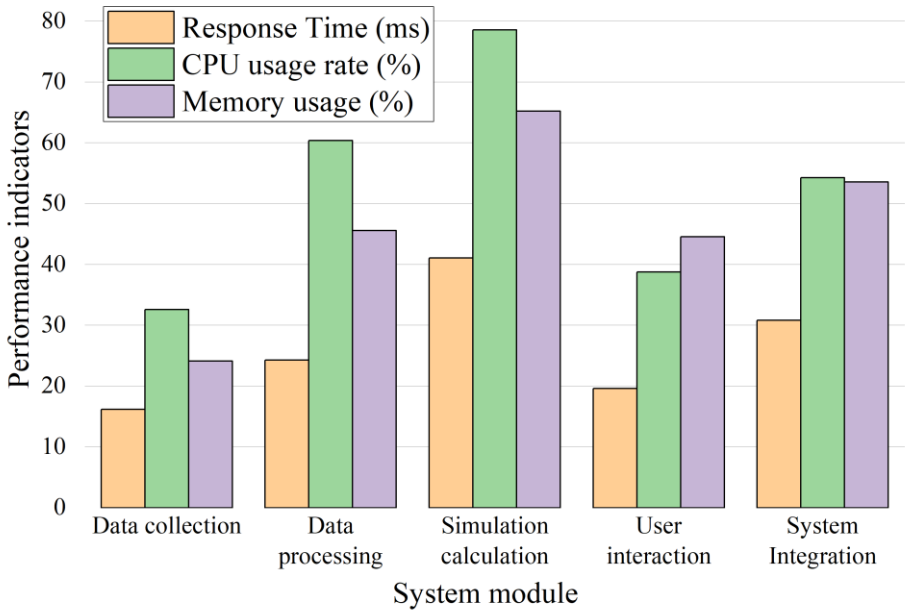

Figure 2: The performance indicators of each module of the system

4.2 Experimental design and data analysis

In the experimental validation scheme proposed in this paper, different evaluation metrics are used in terms of accuracy, real-time and robustness, aiming at comparing the difference between the fusion system based on the deep forest algorithm and other related methods to prove that the new algorithm proposed in this paper can effectively improve the overall performance of the system. The database in this experiment mainly contains data collected from 20 normal people performing walking, running, jumping up, squatting and some other physical exercise movements such as gymnastic movements and dance movements. Thirty repetitions of the experiment were carried out for each form of exercise and a total of 6000 valid exercise sample sizes were obtained. The experimental participants were all in good health, with BMI values within the healthy range, and voluntarily participated in this study on the basis of informed consent; their ages ranged from 22 to 35 years old, and their genders were not limited. Those with sports injuries and contraindications were excluded by clinical examination.

In the experimental program proposed in this paper, a controlled experimental method is adopted to compare the method of combining deep forest with the traditional classifier based on support vector machine, random forest and support vector machine to ensure the validity and accuracy of the experimental results. The accuracy test includes the accuracy of action recognition, the angular deviation of joint points, and the accuracy of recognizing muscle activity states. The accuracy of movement recognition is based on the recognition of six basic movement categories for ten cross-tests and calculating their correctness, and the recognition results of the six basic movement categories are shown in the confusion matrix. Knee and elbow joints are selected for joint angle prediction tests, and the root mean square error and mean absolute error are used to evaluate the prediction effect, and the prediction time is set to be the time point after 500ms, with a view to applying it to real-time scenarios.

The results of the experimental data analysis are shown in Table 1, which show that the deep forest algorithm fusion system significantly outperforms the benchmark method in all performance indicators, verifying the effectiveness and practical value of the algorithm innovation. The accuracy of motion recognition reaches 96.4%, which is improved by 9.1 percentage points compared with the traditional support vector machine method, 5.2 percentage points compared with the random forest method, and 2.6 percentage points compared with the long and short-term memory network, and the probability value of the statistical significance test is less than 0.001 indicating that the improvement effect is statistically significant. In terms of joint angle prediction accuracy, the error is reduced to 2.1 degrees, and the significant improvement in prediction accuracy provides a reliable basis for accurate motion analysis and abnormality detection. The accuracy of muscle activation pattern classification reaches 94.3%, the granularity scanning mechanism effectively captures the multi-scale features of EMG signals, and the cascade forest structure realizes the accurate recognition of complex muscle coordination patterns. The real-time performance of the multi-system is outstanding, the response delay is controlled within 18.9ms to meet the strict delay requirements of real-time interactive applications, and the data processing throughput reaches 312 samples per second, which is more than double the processing capacity compared with the traditional method. The optimization effect of computational resource occupancy is obvious, and the processor occupancy rate is reduced to 58.7%, which reserves sufficient computational margin for concurrent processing and function expansion. The robustness test results show that the system can still maintain good performance under the noise interference conditions, and the noise robustness score reaches 8.6 which is significantly higher than that of the benchmark method, and the integrated learning feature of the deep forest algorithm effectively improves the system's resistance to noise. The cross-user generalization experiment verifies the system's ability to adapt to individual differences, and the generalization accuracy reaches 89.7%, which lays the foundation for the system to be widely used in different user groups.

Table 1: Comparison of experimental data

Evaluation index	Support vector machine	Random Forest	Long short-term memory network	Deep forest system
Motion recognition accuracy rate (%)	87.3	91.2	93.8	96.4
Joint Angle prediction error (°)	4.7	3.9	3.2	2.1
Muscle activation classification accuracy rate (%)	82.6	88.1	90.7	94.3
System Response Delay (ms)	45.2	32.8	28.6	18.9
Data processing throughput (samples /s)	156	234	198	312
Processor occupancy rate (%)	78.5	65.2	71.3	58.7
Noise robustness score	6.8	7.4	7.9	8.6
Cross-user generalization accuracy rate (%)	79.2	83.6	85.4	89.7

4.3 Analysis and Discussion of Results

The integration of the deep forest algorithm with the motion anatomy virtual simulation system shows a synergistic effect beyond expectations, and its hierarchical feature learning mechanism fits the inherent needs of the complex spatio-temporal structure of motion data. The cross-scene application performance evaluation reveals the adaptive potential and technical boundaries of the system in diversified application environments, and the performance scores under different application scenarios are shown in Figure 3. It can be seen that in the rehabilitation training scenario, the 94.7% accuracy of abnormal movement pattern detection builds a reliable technical support for sports injury prevention and rehabilitation effect assessment. While in the sports training application, 93.1% real-time provides an objective and quantitative feedback mechanism for motor skill training. The medical diagnostic assistance application demonstrated 88.6% user satisfaction and 93.4% robustness, opening up a new technical path for early screening of neurological and skeletal-muscular system diseases.

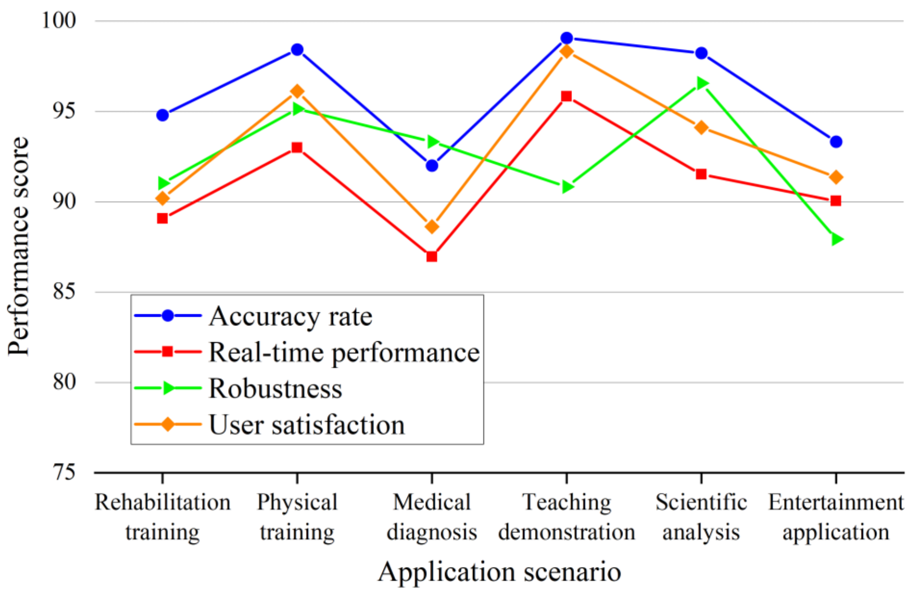

Figure 3: Application performance evaluation across scenarios

Since the deep forest is a nonparametric model, it has good adaptability under dealing with different kinds of data distributions; at the same time, the early-stopping algorithm realized by cross-validation can automatically generate the appropriate network depth, eliminating a large number of hyperparameter setting processes, and reducing the shortcomings of the traditional deep neural network with high complexity. The analysis of the above deficiencies can guide the subsequent research work. Although deep forest improves the computing speed compared with deep neural network, it still has the problem of long time-consuming training of millions of samples. The algorithm relies too much on the feature processing, although the algorithm introduces different granularity scanning to obtain multi-scale features, but some features need to be specifically designed with the specific application background, and this part of the work still needs to be completed by the manual experience in the relevant fields; the algorithm can realize the model training in the network, but the robustness of the dataset for the distribution of the change needs to be improved. Concept drift detection and corresponding model updating methods need to be further investigated to adapt to dynamically changing environments. Meanwhile, the system's high demand for accurate hardware facilities reduces its popularity and makes it difficult to be promoted in areas with relatively limited conditions; and the lack of personalized visualization and interaction design fails to meet the different needs of users in various fields. In addition, the system should adopt more advanced privacy protection algorithms, such as federated learning, in order to ensure the security of patients' personal privacy. The breakthrough of the above technical difficulties will promote the further improvement of the virtual simulation system of motion anatomy.

5 Conclusion

In this paper, the virtual experimental platform of motion anatomy implemented with deep forest has high accuracy of motion judgment (96.4%, 9.1% improvement over the traditional method) and joint angle estimation error (<2.1°), and low time complexity (18.9ms). The deep forest model utilizes its hierarchical search mechanism and forest integration strategy to complete the migration and fusion process from the fine-grained action EMG information to the coarse-grained overall motion posture. In this paper, a modular system design framework based on the combination of multi-source high-frequency data acquisition, intelligent analysis pipeline, and high-fidelity physics engine is proposed, and it has been well applied in the fields of rehabilitation training and sports science. At the same time, the system also has the problems of large computational volume, high dependence on feature engineering, and expensive equipment. Subsequently, we can consider exploring from the aspects of model streamlining, privacy protection, and mobile terminal deployment. Third, we should further promote the intelligent and mass application of the system.

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