Computer-Aided Design AND APPLICATIONS

Collaborative CAD in Cloud Classroom for Personalized User Recommendations Through Cloud Computing and Behavior Modeling

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Abstract. To improve the quality of online English teaching, cloud computing technology is combined to analyze student behavior in English cloud classroom teaching. Moreover, this paper uses behavior modeling to identify student behaviors, recommend teaching resources, and select the Hill muscle model to study muscle contraction dynamics. In addition, the human body is simplified as a rigid body model when analyzing the human body motion from the perspective of inverse dynamics. The experimental research shows that the target user recommendation system of English cloud classrooms based on cloud computing and behavior modeling proposed in this paper can effectively improve the quality of English online teaching.

Keywords: Cloud Computing; Behavior Modeling; English; Cloud Classroom; User Recommendation; Collaborative CAD.
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1 INTRODUCTION

The openness and online nature of English online teaching enable learners to study online courses anytime and anywhere. However, due to the lack of effective communication and supervision mechanisms between teachers and students in the current English online teaching platform, learners need to have strong self-control to ensure a high course participation rate. The premise and key to realizing early and accurate prediction of learner behavior is to master the learner's learning rules and actual learning situation and also to provide support for appropriate personalized learning intervention and guidance.

It is observed from the data of English online teaching that some learners prefer to start with basic knowledge and evaluate the mastery of knowledge points through coursework and quizzes. Therefore, how to describe and model the abstract learning patterns from the massive learning behavior data and then understand and infer the learners' potential learning motivation is a problem worthy of research.

In the field of educational psychology, educators believe that the characteristics of learning behavior displayed by learners are strongly related to learning motivation and purpose, and the learning behavior patterns of different learners are different. In educational psychology, learning style theory is often used to describe learners' preferred ways of acquiring, processing, interpreting, organizing, and analyzing knowledge.

The current research on learners' learning patterns in English online teaching is mostly based on statistical methods, which analyze the correlation between learners' background information, learning behavior characteristics, learning motivation, and learning intentions. There is a lack of research on quantitative modeling of patterns. Therefore, this study will analyze the relationship between multi-dimensional learning behavior characteristics and diverse learning outcomes from a data-driven perspective. On the basis of the data analysis results and guided by the learning style theory in educational psychology, a potential learning style model is proposed to realize the identification and modeling of group learning styles in English online teaching.

This paper combines cloud computing technology to analyze student behavior in English cloud classroom teaching, recognizes student behavior through behavior modeling, and recommends appropriate learning materials and learning methods to users through data processing to improve the efficiency of English online teaching.

2 RELATED WORK

Literature [13] proposed a learner behavior classification system to test the relationship between different learning behavior patterns and learning levels and found that learners' course participation behavior can be classified into the following styles: viewers, solvers, all-rounders, collectors, and bystanders. At the same time, the author designs two incentive mechanisms in the course forum to enhance learners' course activity, and the effectiveness of the incentive mechanism is verified through experiments. Literature [5] conducted the following three research on learners who registered for the same course but used different languages: 1) the learner's learning motivation; 2) the relationship between the learner's learning motivation and different course participation modes 3) Based on the learning motivation, analyze the learning characteristics of the learners who have completed the course. Literature [3] studies the participation mode of learners in the FutureLearn MOOC platform. The FutureLearn MOOC platform is based on social constructivist pedagogy and takes the course discussion area as its main section. The study found that the MOOC platform adopts The pedagogical theory that has an impact on learners' course participation patterns. Reference [7] extracts the learning trajectory of the learner in the longitudinal mode according to the interaction behavior of the learner with the resources such as course videos, coursework, and course examinations and combines the background information of the learner (such as age, gender, education level, etc.) The interactive behavior data in the course forum, etc., divide the learners into four types: Completing, Auditing, Disengaging and Sampling.

Reference [8] uses N-gram language model to mine typical learning behavior combinations and at the same time, identifies common learning behavior sequences to implement learning strategy recommendations. The author finds that different behavioral patterns are correlated with learners' course success, regards learners' course participation behaviors as hidden variables, and finds course contextual information (such as learners' background information characteristics, length of study time, etc.) through analysis.) has a certain correlation with the type of learning behavior. Literature [11] analyzes the learning behavior data of the learners with qualified grades in the course and finds that academic performance is related to the number of posts in the course forum, the completion of the mutual assessment of coursework, the number of coursework submissions, and the learners' participation in the test. circumstances are related. The study also found that the learners who were excellent and qualified in task learning behaviors mostly had good study habits. In terms of interactive learning behavior and learning participation, learners with excellent grades are more motivated than those with qualified grades to participate in discussions in course forums and conduct peer evaluations. Literature [17] studied the relationship between the goals of learners registering for courses and the characteristics of learning behavior, and the influence of different disciplines on the retention rate and completion rate of learners. The results show that the learning goals of learners will affect the success rate of course participation, and There are differences in learners' participation behaviors and learning goals in courses of different subjects. Literature [6] classifies learners according to the characteristics of learners' learning behavior in the English MOOC platform and studies the relationship between learning behavior and the learning effect.

Literature [1] studied learners' learning motivation, learning mode and a series of factors that affect learners' return to MOOCs to continue learning, and realized the understanding and explanation of the reasons for learners' withdrawal behavior. Literature [2] integrates learners, teachers, and learning support systems in individual learning and proposes a model to describe and explain learners' participation behavior and retention behavior in MOOCs. Reference [18] analyzes and understands learning behavior based on the data of learners' responses in the course questionnaire. Reference [12] treats the interaction between learners and course content in the form of "bagofinteractions", and proposes a probabilistic topic model to cluster learners according to learners' learning behaviors, so as to realize the interpretability of learners' learning behavior patterns. Express.

Reference [14] used a linear regression model to investigate the relationship between learners' different learning strategies and diverse background information in MOOCs and found that learners' nationality attributes were related to the completion of course content. Certificated learners skip about 22% of course content, and these learners typically use nonlinear navigation strategies to jump to already-learned course content for repetitive learning. The authors also analyzed the relationship between teacher-student ratio and nationality and found that learners from countries with low teacher-student ratios had a higher frequency of reviewing course content. Literature [15] found that learners from different countries and regions with different genders have significant differences in the proportion of completing courses and obtaining course certificates in the MOOC learning process. Reference [10] analyzed the relationship between nationality and cultural differences and learners' academic performance, and the analysis was based on the following three learning behaviors: the interaction between learners and course content, the behavior of learners completing exams, and the learners' behavior in courses. Information about the closest friends in the forum. The authors found that after clustering learners according to the above three learner behaviors, each category is correlated with different nationalities and their corresponding cultures.

3 MODELING OF STUDENT BEHAVIOR BASED ON SKELETAL MUSCLE MODEL

The skeletal muscle model based on biomechanics describes the transformation relationship between muscle activation, muscle contraction force, and joint torque. It consists of three sub-models: the muscle activation dynamics model, the muscle contraction dynamics model, and the skeletal muscle geometry model. This paper selects the Hill muscle model to study the dynamics of muscle contraction in the process of modeling student behavior.

As shown in Figure 1, the Hill model believes that tendons and muscle fibers are in series structure, and muscle fibers mainly include two parts: the contractile element that generates the active contraction force F_a^m and the passive element that generates the passive contraction force F_p^m, both of which are in a parallel structure. As can be seen from Figure 1, the relationship between the total muscle contraction force F, the force F^{mt} at the end of the tendon and the contraction force F^{m} generated by the muscle fibers is as follows:

$$F = F^{mt} = F^{m}\cos\varphi \tag{1}$$

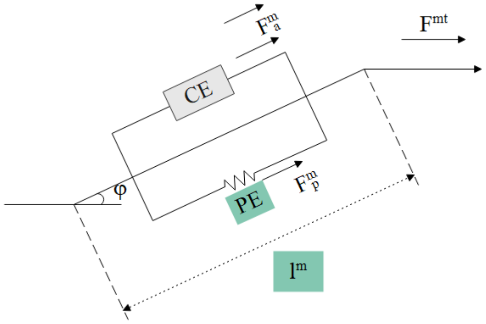

Figure 1: Hill muscle model.

Among them, φ is the angle between the muscle fiber and the tendon, called the pinnate angle. Therefore, the pinnate angle values of the six muscles involved in this paper refer to the relevant values in the references.

Muscle fiber contractility can be expressed as[4]:

$$F^{m} = \left(f_a(l)\cdot f_a(v)\cdot a + f_p(l)\right)\cdot F_{\max^{m}} \tag{2}$$

$$l = \frac{l^{m}}{l_o^{m}} \tag{3}$$

$$v = \frac{v^{m}}{v_{\max^{m}}} \tag{4}$$

Among them, $F_{\max}^{m}$ is the maximum isometric contraction force of the muscle, and a is the degree of muscle activation. l is the normalized muscle fiber length, l^{m} is the changed muscle fiber length, and l_O^{m} is the optimal muscle fiber length. v is the normalized muscle fiber contraction velocity, v^{m} is the variable muscle fiber contraction velocity, and $v_{\max^{m}}$ is the maximum muscle fiber contraction velocity. $f_a(l)$ represents the relationship between active contraction force and normalized muscle fiber length, $f_a(v)$ represents the relationship between active contraction force and muscle fiber contraction velocity, and $f_p(l)$ represents the relationship between passive contraction force and muscle fiber length. These three relationships are formulated as[16]:

$$f_a(l) = e^{-2(l-1)^2} \tag{5}$$

$$f_a(v) = \begin{cases} \frac{1+v}{1-4v}, & v \le 0 \\ \frac{0.8+18v}{0.8+10v}, & v > 0 \end{cases} \tag{6}$$

$$f_p(l) = \frac{e^{4(l-1)/0.6} - 1}{e^4 - 1} \tag{7}$$

According to the above analysis, we assume that the constant physiological parameter values of $F_{\max^m}$、l_O^m、$v_{\max^m}$ are known. As long as the value of the muscle fiber contraction length l^m and the muscle fiber contraction speed v^m are obtained, the muscle contraction force can be calculated by formula (2). However, it is very difficult to obtain the actual l^m and v^m during the experiment.

After obtaining the muscle force and the moment arm of each muscle relative to the joint, the joint torque can be calculated by formula (8).

$$T = \sum_{i=1}^{6} \left(F_{\text{flex } i} - F_{\text{ext } i} \right) \cdot r_i \tag{8}$$

Among them, $F_{\text{flex. } i}$ represents the muscle force calculated from the activation degree of the muscle corresponding to the flexion action part, and $F_{\text{ext.i}}$ represents the muscle force calculated from the activation degree of the muscle corresponding to the stretching movement process. r_i represents the moment arm of the muscle relative to the joint. When calculating the elbow joint moment, r_i represents the moment arm of the muscle relative to the elbow joint. When calculating the wrist moment, r_i represents the force of the muscle relative to the wrist.

When analyzing the motion of the human body from the perspective of inverse dynamics, it is usually necessary to simplify the human body into a rigid body model. Figure 2 is a simplified rigid body model of the upper limbs of the human body. We use the Lagrangian method to analyze the inverse dynamics without transforming the coordinate system, and the solution process is simple and clear. Therefore, the Lagrangian method is used in this paper to analyze the upper limb dynamics. The Lagrangian method solves the dynamical problem through the Lagrangian equation from the perspective of the energy of the system. The general form of the Lagrange equation is:

$$F_i = \frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i} \right) - \frac{\partial L}{\partial q_i} \tag{9}$$

Among them, F_i is the generalized force, q_i is the generalized coordinate, and L is called the Lagrangian function, which is the difference between the kinetic energy and the potential energy of the system. In figure 3, the rotation center of the elbow joint is taken as the origin of the coordinate system, l_1 represents the length of the forearm, l_2 represents the length of the hand (the palm and fingers are regarded as a whole in this study), d_1 represents the distance from the center of mass of the front yoke to the center of the elbow joint, d_2 represents the distance from the center of mass of the hand to the center of the wrist joint, d_2 and θ_2 represent two generalized coordinates, respectively. The masses of the front and the hand are m_1, m_2, respectively. We assume that the centroids of the front ridge and the hand are C_1, C_2, respectively, and their coordinates are $(x_1, y_1), (x_2, y_2)$, respectively, as follows[9]:

$$\begin{cases} x_1 = d_1 \sin\theta_1 \\ y_1 = -d_1 \cos\theta_1 \end{cases} \tag{10}$$

$$\begin{cases} x_2 = l_1 \sin\theta_1 + d_2 \sin\theta_2 \\ y_2 = -l_1 \cos\theta_1 - d_2 \cos\theta_2 \end{cases} \tag{11}$$

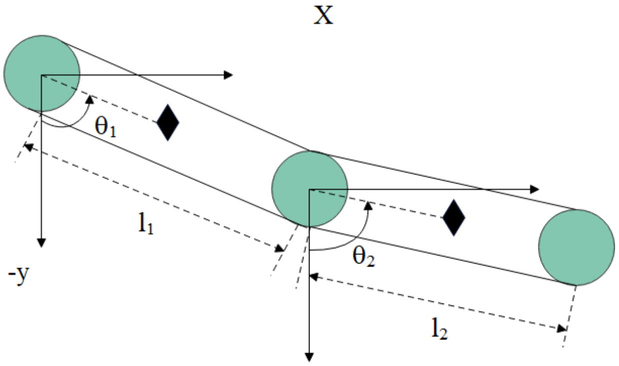

Figure 2: Simplified rigid body model of human upper limbs.

The center of mass position coordinate change can be obtained from formulas (10) and (11). Taking the derivative with respect to time, the equation of motion of the center of mass can be obtained:

$$\begin{cases} \dot{x}_1 = d_1 \cos\theta_1 \cdot \dot{\theta}_1 \\ \dot{y}_1 = d_1 \sin\theta_1 \cdot \dot{\theta}_1 \end{cases} \tag{12}$$

$$\begin{cases} \dot{x}_2 = l_1 \cos\theta_1 \cdot \dot{\theta}_1 + d_2 \cos\theta_2 \cdot \dot{\theta}_2 \\ \dot{y}_2 = l_1 \sin\theta_1 \cdot \dot{\theta}_1 + d_2 \sin\theta_2 \cdot \dot{\theta}_2 \end{cases} \tag{13}$$

Combining formulas (12) and (13), the velocity of the two centroids can be calculated as:

$$v_1 = \sqrt{\dot{x}_1^2 + \dot{y}_1^2} = d_1\dot{\theta}_1 \tag{14}$$

$$v_2 = \sqrt{\dot{x}_2^2 + \dot{y}_2^2} = \sqrt{\left(l_1\dot{\theta}_1\right)^2 + \left(d_2\dot{\theta}_2\right)^2 + 2l_1d_2\dot{\theta}_1\dot{\theta}_2\cos\left(\theta_2 - \theta_1\right)} \tag{15}$$

From this, the kinetic energy $T = T_1 + T_2$ of the system can be obtained, T_1 is the kinetic energy of the forearm, and T_2 is the kinetic energy of the hand.

$$T_1 = \frac{1}{2}m_1v_1^2 = \frac{1}{2}m_1d_1^2\dot{\theta}_1^2 \tag{16}$$

$$T_2 = \frac{1}{2}m_2v_2^2 = \frac{1}{2}m_2\left[\left(l_1\dot{\theta}_1\right)^2 + \left(d_2\dot{\theta}_2\right)^2 + 2l_1d_2\dot{\theta}_1\dot{\theta}_2\cos\left(\theta_2 - \theta_1\right)\right] \tag{17}$$

After obtaining the kinetic energy of the system, it is necessary to obtain the potential energy of the system $V = V_1 + V_2$. V_1 is the kinetic energy of the front yoke, and V_2 is the kinetic energy of the hand.

$$V_1 = -m_1gd_1\cos\theta_1 \tag{18}$$

$$V_2 = -m_2g\left(l_1\cos\theta_1 + d_2\cos\theta_2\right) \tag{19}$$

Therefore, the Lagrangian function of the system can be obtained as:

$$L = T - V = \frac{1}{2}m_1d_1^2\dot{\theta}_1^2 + \frac{1}{2}m_2\left[\left(l_1\dot{\theta}_1\right)^2 + \left(d_2\dot{\theta}_2\right)^2 + 2l_1d_2\dot{\theta}_1\dot{\theta}_2\cos\left(\theta_2 - \theta_1\right)\right] + m_1gd_1\cos\theta_1 + -m_2g\left(l_1\cos\theta_1 + d_2\cos\theta_2\right) \tag{20}$$

According to the Lagrange equation, the partial derivatives of $\dot{\theta}_1, \dot{\theta}_2$ and θ_1, θ_2 are obtained respectively:

$$\frac{\partial L}{\partial\dot{\theta}_1} = \left(m_1d_1^2 + m_2l_1^2\right)\dot{\theta}_1 + m_2l_1d_2\dot{\theta}_2\cos\left(\theta_2 - \theta_1\right) \tag{21}$$

$$\frac{\partial L}{\partial\dot{\theta}_2} = m_2d_2^2\dot{\theta}_2 + m_2l_1d_2\dot{\theta}_1\cos\left(\theta_2 - \theta_1\right) \tag{22}$$

$$\frac{\partial L}{\partial\theta_1} = -\left(m_1gd_1 + m_2gl_1\right)\sin\theta_1 + m_2l_1d_2\dot{\theta}_1\dot{\theta}_2\sin\left(\theta_2 - \theta_1\right) \tag{23}$$

$$\frac{\partial L}{\partial\theta_2} = -m_2gd_2\sin\theta_2 - m_2l_1d_2\dot{\theta}_1\dot{\theta}_2\sin\left(\theta_2 - \theta_1\right) \tag{24}$$

Then taking the derivation, we can get:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}_1}\right)=\left(m_1 d_1^2+m_2 l_1^2\right)\ddot{\theta}_1+m_2 l_1 d_2 \ddot{\theta}_2 \cos\left(\theta_2-\theta_1\right)$$
$$-m_2 l_1 d_2 \dot{\theta}_2^2 \sin\left(\theta_2-\theta_1\right)+m_2 l_1 d_2 \dot{\theta}_1 \dot{\theta}_2 \sin\left(\theta_2-\theta_1\right) \tag{25}$$

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}_2}\right)=m_2 d_2^2 \ddot{\theta}_2+m_2 l_1 d_2 \ddot{\theta}_1 \cos\left(\theta_2-\theta_1\right)$$
$$+m_2 l_1 d_2 \dot{\theta}_1^2 \sin\left(\theta_2-\theta_1\right)-m_2 l_1 d_2 \dot{\theta}_1 \dot{\theta}_2 \sin\left(\theta_2-\theta_1\right) \tag{26}$$

Substituting into the Lagrange equation, we have:

$$\begin{cases} T_e=\dfrac{d}{dt}\left(\dfrac{\partial L}{\partial \dot{\theta}_1}\right)-\dfrac{\partial L}{\partial \theta_1} \\ T_w=\dfrac{d}{dt}\left(\dfrac{\partial L}{\partial \dot{\theta}_2}\right)-\dfrac{\partial L}{\partial \theta_2} \end{cases} \tag{27}$$

From this, the moment of the two joints can be obtained from the inverse dynamics calculation:

$$\begin{cases} T_e=\left(m_1 d_1^2+m_2 l_1^2\right)\ddot{\theta}_1+m_2 l_1 d_2 \ddot{\theta}_2 \cos\left(\theta_2-\theta_1\right) \\ -m_2 l_1 d_2 \dot{\theta}_2^2 \sin\left(\theta_2-\theta_1\right)+\left(m_1 g d_1+m_2 g l_1\right)\sin\theta_1 \\ T_w=m_2 d_2^2 \ddot{\theta}_2+m_2 l_1 d_2 \ddot{\theta}_1 \cos\left(\theta_2-\theta_1\right) \\ +m_2 l_1 d_2 \dot{\theta}_1^2 \sin\left(\theta_2-\theta_1\right)+m_2 g d_2 \sin\theta_2 \end{cases} \tag{28}$$

In formula (28), T_e represents the moment of the elbow joint, and T_w represents the moment of the wrist joint. The m_1, m_2, l_1, d_1 and d_2 involved in the formula are the physical parameters of the human body, which can be estimated according to the national standard of the inertial parameters of the human body. The standard establishes a binary regression equation of the mass, centroid position, and height and weight of each body part of Chinese adults:

$$Y=B_0+B_1 X_1+B_2 X_2 \tag{29}$$

Among them, B_0 is the constant term of the binary regression equation, B_1 is the regression coefficient of weight and B_2 is the regression coefficient of height. X_1、X_2 represent weight and height, respectively, in kg and mm.

Combined with the comprehensive analysis of the forward biomechanical skeletal muscle model and the reverse dynamics, the model parameter identification roadmap in Figure 3 can be obtained.

In this study, six muscles (ECRL, ECU, FCR, FCU, BIC, and TRI) have been selected to play a major role in the flexion and extension of the elbow and wrist joints through the knowledge of exercise physiology and anatomy. Each muscle involves 7 parameters to be adjusted (d、c_1、c_2、A、$F_{\max^m}$、l_0^m and $v_{\max^m}$), and the entire model will need to identify 42 parameters, which will greatly increase the complexity of parameter identification. Usually, $v_{\max^m}$ can be replaced by $10l_O^m$. In addition, through multiple experiments, it is found that the values of the four parameters d、c_1、c_2、A have little effect on the activation characteristics of different muscles. Therefore, different muscles of the same subject can share the same value. Finally, the parameters that each subject needs to identify are d、c_1、c_2、A and the respective $F_{\max^m}$ and l_O^m values of the 6 muscles, which have 16 values in total.

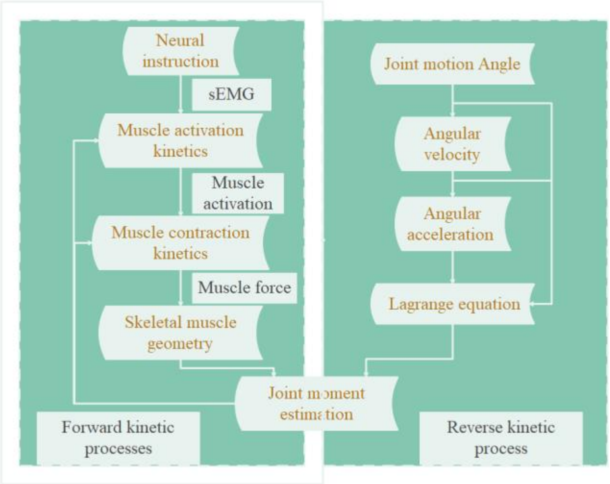

Figure 3: Parameter identification roadmap.

Many researchers have used intelligent biological evolutionary algorithms, such as genetic algorithms, to identify the parameters of skeletal muscle models. The skeletal muscle model established in this paper involves many physiological parameters, and the traditional biological evolution algorithm will greatly reduce the model's operating efficiency.

Kalman filtering is an algorithm that extracts the estimated value through the observation quantity based on the minimum variance estimation criterion. Kalman filter algorithms commonly used for parameter online identification include EKF and UKF. EKF needs to obtain the Jacobian matrix and Hessian matrix of the nonlinear system, which not only requires a large amount of calculation, but also has limitations in the application of some complex nonlinear systems. UKF does not need to derive the Jacobian matrix of the system, the calculation process is simple, and it is widely used in the online parameter identification of nonlinear systems. Therefore, this paper chooses UKF to identify the model parameters.

UT transform plays a very important role in the UKF realization process. The basic method of UT implementation is: according to certain rules, a partial set of points (called Sigma points) is taken in the original state distribution. These point sets are substituted into the nonlinear system to obtain the corresponding function value point set, and then the mean and covariance of the function value point set are used to simulate the mean and covariance of the real function value. Its schematic diagram is shown in Figure 4.

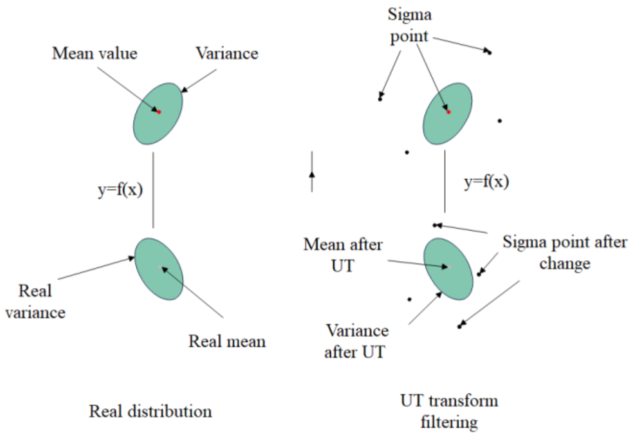

Figure 4: UT transformation schematic diagram.

When taking Sigma points, the commonly used strategies are symmetric sampling, variable scale sampling, single-line sampling, and so on. In this paper, a symmetric sampling strategy is used for UT transformation.

We assume that there is a nonlinear system $\mathbf{y} = f(\mathbf{x})$, the n-dimensional state variable $\mathbf{x}$ and its mean value $\bar{\mathbf{x}}$ are known, and the variance is $\mathbf{P}$. The 2n+1 Sigma points $\mathbf{X}$ and the weight values ω corresponding to the sampling points can be obtained according to formulas (30) and (31).

$$\begin{cases} \mathbf{X}^{(0)} = \overline{\mathbf{X}} \\ \mathbf{X}^{(i)} = \overline{\mathbf{X}} + (\sqrt{(n+\lambda)\mathbf{P}})_i, i \in [1, n] \\ \mathbf{X}^{(j)} = \overline{\mathbf{X}} - (\sqrt{(n+\lambda)\mathbf{P}})_j, j \in [n+1, 2n] \end{cases} \tag{30}$$

$$\begin{cases} w_m^{(0)} = \dfrac{\lambda}{n+\lambda} \\ w_c^{(0)} = \dfrac{\lambda}{n+\lambda} + \left(1-\alpha^2+\beta\right) \\ w_m^{(i)} = w_c^{(i)} = \dfrac{\lambda}{2(n+\lambda)}, i \in [1, 2n] \end{cases} \tag{31}$$

Among them, the subscript m represents the mean, and c represents the covariance. $\lambda = \alpha^2(n+\kappa) - n$ is the scaling parameter, which can adjust the prediction error. $\alpha \in [0,1]$ represents the distribution state of the Sigma point, and κ is the adjustment parameter. The values of α,κ need to ensure that the matrix $(n+\lambda)\mathbf{P}$ is positive semi-definite. $\beta \geq 0$, its value will affect the precision of variance. When the variable is a Gaussian distribution, the optimal value of β that can be obtained is 2. $(\sqrt{(n+\lambda)\mathbf{P}})_i$ is the i-th row of the square root of matrix $(n+\lambda)\mathbf{P}$.

The state variables and observation variables in this paper are:

$$\mathbf{X} = \left[\mathbf{F}_{m\_w}^{\mathrm{T}}, \mathbf{F}_{m\_e}^{\mathrm{T}}, \mathbf{F}_{\max^{\mathrm{T}}}, \mathbf{L}_o^{\mathrm{T}}, d, c_1, c_2, A\right] \tag{32}$$

$$\mathbf{Z} = \left[\mathbf{T}_e, \mathbf{T}_w\right] \tag{33}$$

Among them, $\mathbf{F}_m^{\mathrm{T}} = \left(F_m^1 w' F_m^2, \cdots F_{m\,w}^6\right)^{\mathrm{T}}$ in the state variable represents the muscle force produced by the 6 muscles on the wrist joint. $\mathbf{F}_{me}^{\mathrm{T}} = \left(F_m^1, F_m^2, \cdots F_{me}^6\right)^{\mathrm{T}}$ represents the muscle force produced by 6 muscles on the elbow joint. $\mathbf{F}_{\max^{\mathrm{T}}} = \left(F_{\max^1}, F_{\max^2}, \cdots F_{\max^6}\right)^{\mathrm{T}}$ represents the maximum isometric contraction force of the 6 muscles, and $\mathbf{L}_{\max^{\mathrm{T}}} = \left(l_{\max^1}, l_{\max^2}, \cdots l_{\max^6}\right)^{\mathrm{T}}$ represents the optimal muscle fiber length of the 6 muscles. The two vectors in the observed variables represent the joint moments obtained by inverse dynamics for the elbow and wrist joints, respectively.

We assume that the existing state equation and observation equation are:

$$\mathbf{X}_{k+1} = f\left(\mathbf{X}_k, \mathbf{a}_k\right) + \mathbf{W}_k \tag{34}$$

$$\mathbf{Z}_{k+1} = f\left(\mathbf{X}_k, \boldsymbol{\theta}_k\right) + \mathbf{V}_k \tag{35}$$

Among them, a is the calculated muscle activation degree, and W is the process noise. Since the vectors contained in the state variables in this paper are muscle force and parameters to be identified, the influence of process noise is not considered. The conversion relationship of muscle force in state variables refers to formula (2) in Section 1.1. $\theta = \left(\theta_e, \theta_w\right)$ is the angle of motion of the elbow and wrist joints. $\mathbf{V}_k$ is the measurement noise, and in general, $\mathbf{V}_k N(0,\mathbf{R}), \mathbf{R}$ is the observation noise covariance matrix. In this study, the variances of the measurement noise corresponding to the two observed variables are set as R_1, R_2.

Therefore, the parameter identification process based on UKF is:

1. The algorithm initializes the state variable $\mathbf{X}^{(0)}$.

2. According to formulas (30) and (31), the algorithm obtains a set of Sigma point sets and their corresponding weights, as follows:

$$\mathbf{X}_{k|k}^{(i)} = \left[\mathbf{X}_{k|k} \quad \mathbf{X}_{k|k} + \sqrt{(n+\lambda)\mathbf{P}_{k|k}}\,\mathbf{X}_{k|k} - \sqrt{(n+\lambda)\mathbf{P}_{k|k}}\right] \tag{36}$$

3. The algorithm calculates the further prediction of 2n+1 Sigma point sets, $i \in [1, 2n+1]$.

4. The algorithm predicts the next state variable through the state relationship of the current state variable, and obtains the further state variable and its covariance matrix by formula (37).

$$\mathbf{X}_{k+1|k} = \sum_{i=0}^{2n} \omega^{(i)} \mathbf{X}_{k+1|k}^{(i)}$$
$$\mathbf{P}_{k+1|k} = \sum_{i=0}^{2n} \omega^{(i)} \left[\mathbf{X}_{k+1|k} - \mathbf{X}_{k+1|k}^{(i)} \right] \left[\mathbf{X}_{k+1|k} - \mathbf{X}_{k+1|k}^{(i)} \right]^{\mathrm{T}} \tag{37}$$

5. The algorithm uses the UT transformation of the predicted value $\mathbf{X}_{k+1|k}$ obtained in step 4. again to generate a new Sigma point set.

6. The algorithm substitutes the point set obtained in step (5) into the observation equation to obtain the predicted observed value, obtains the mean of the predicted value through formula (38), and obtains its covariance through formulas (39) and (40).

$$\overline{\mathbf{Z}}_{k+1|k} = \sum_{i=0}^{2n} \omega^{(i)} \mathbf{Z}_{k+1|k}^{(i)} \tag{38}$$

$$\mathbf{P}_{z_k z_k} = \sum_{i=0}^{2n} \omega^{(i)} \left[\mathbf{Z}_{k+1|k}^{(i)} - \overline{\mathbf{Z}}_{k+1k}^{*} \right] \left[\mathbf{Z}_{k+1k}^{(i)} - \overline{\mathbf{Z}}_{k+1k}^{*} \right]^{\mathrm{T}} \tag{39}$$

$$\mathbf{P}_{x_k z_k} = \sum_{i=0}^{2n} \omega^{(i)} \left[\mathbf{X}_{k+1k}^{(i)} - \overline{\mathbf{Z}}_{k+1|k} \right] \left[\mathbf{X}_{k+1k}^{(i)} - \overline{\mathbf{Z}}_{k+1k} \right]^{\mathrm{T}} \tag{40}$$

7. The algorithm calculates the Kalman gain as follows:

$$\mathbf{K}_{k+1} = \mathbf{P}_{x_k z_k} \mathbf{P}_{x_k z_k}^{-1} \tag{41}$$

8. The algorithm updates the state variables and covariance according to formula (42).

$$\mathbf{X}_{k+1|k+1} = \mathbf{X}_{k+1|k} + \mathbf{K}_{k+1} \left[\mathbf{Z}_{k+1} - \mathbf{Z}_{k+1} \right]$$
$$\mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} - \mathbf{K}_{k+1} \mathbf{P}_{z_k z_k} \mathbf{K}_{k+1}^{\mathrm{T}} \tag{42}$$

Through experiments, it is found that the value of observation noise variance R_1, R_2 will affect the accuracy and yield of parameter identification. In order to seek the optimal parameter identification results, this paper uses the differential evolution algorithm (DE) to optimize the values of R_1, R_2.

The DE algorithm is an intelligent optimization algorithm that simulates the biological evolution process, and seeks the global optimal solution through the criterion of survival of the fittest. The main work includes three operations of mutation, crossover and selection. The DE algorithm is also often used in the parameter identification of skeletal muscle models. The flow of the DE algorithm is shown in Figure 5.

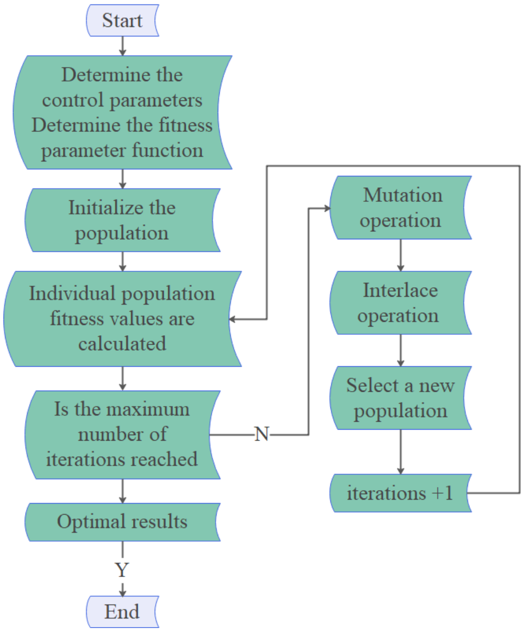

Figure 5: DE algorithm flow chart.

It can be seen from the implementation process of the DE algorithm that the setting of the fitness function is very critical. The values of R_1, R_2 will affect the result of parameter identification and then the estimation of joint torque. Therefore, the fitness function in this paper is set as the global root mean square error (Root Mean Square Error, RMSE) between the estimated moment and the reference moment.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}\left(T_i(t) - \hat{T}_i(t)\right)^2}{N}} \tag{43}$$

Among them, N is the number of samples, $T_i(t)$ is the reference torque of the elbow-wrist joint, and $\hat{T}_i(t)$ is the estimated torque. The structure of UKF based on DE optimization is shown in Figure 6.

4 RECOMMENDATION OF TARGET USERS IN ENGLISH CLOUD CLASSROOM BASED ON CLOUD COMPUTING AND BEHAVIOR MODELING

This paper designs a general network English learning behavior acquisition module based on a cloud computing module and uses AJAX technology to collect and transmit learners' behavior information. Moreover, it integrates data collection, identification, and storage functions and has the ability to export data in XML format so that data can be shared on heterogeneous platforms.

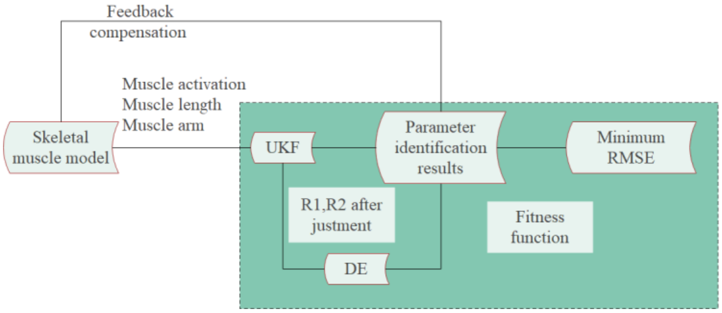

Figure 6: DE-UKF optimized structure.

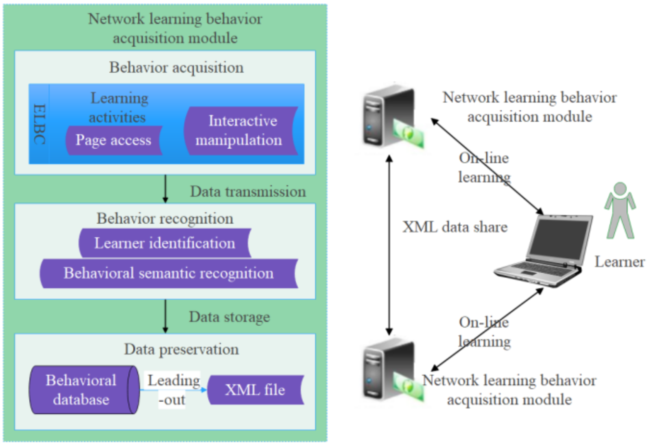

Figure 7: The overall structure of the English online learning behavior collection module.

Figure 8 is a schematic diagram of student target recognition in English cloud classrooms based on cloud computing and behavior modeling.

(a) Grayscale image of English cloud classroom

(b) Target feature recognition in English cloud classroom

Figure 8: Schematic diagram of student target recognition in English cloud classroom based on cloud computing and behavior modelling.

Through the above research, it is verified that the target recognition of English cloud classroom students based on cloud computing and behavior modeling has certain effects. After that, the construction of the English teaching resource recommendation system is carried out, and the schematic diagram of the complete personalized teaching resource recommendation system is shown in Figure 9.

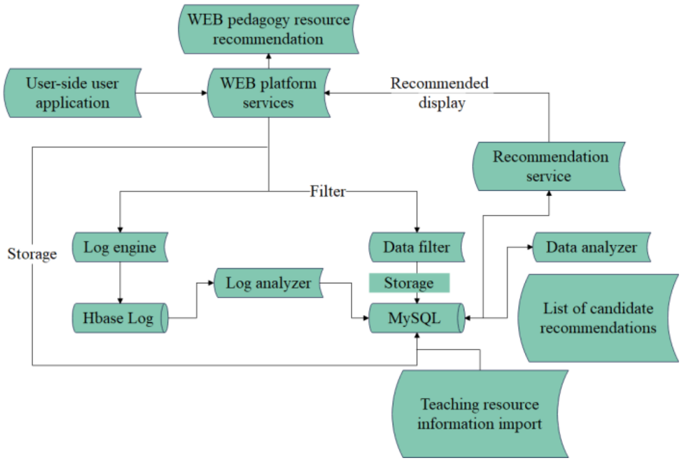

Figure 9: Structure diagram of the recommendation system.

The effect of the recommendation system is verified, and the student feature recognition and learning resource recommendation effect of the system are verified through simulation experiments, and the simulation test results shown in Table 1 are obtained.

NO	*Behavior recognition*	*Recommended effect*	*NO*	*Behavior recognition*	*Recommended effect*

1	*78.88*	*78.56*	*21*	*75.15*	*81.37*
2	*86.82*	*82.18*	*22*	*71.04*	*78.34*
3	*81.78*	*76.87*	*23*	*81.06*	*75.79*
4	*85.56*	*82.57*	*24*	*75.69*	*73.34*
5	*75.28*	*73.84*	*25*	*84.27*	*75.34*
6	*77.71*	*77.79*	*26*	*83.04*	*72.48*
7	*83.47*	*79.84*	*27*	*79.90*	*84.50*
8	*85.58*	*79.37*	*28*	*79.27*	*85.43*
9	*84.05*	*81.99*	*29*	*84.63*	*77.57*
10	*79.98*	*73.27*	*30*	*78.36*	*85.03*
11	*79.73*	*71.82*	*31*	*82.02*	*76.82*
12	*80.62*	*81.84*	*32*	*71.67*	*80.86*
13	*85.34*	*73.23*	*33*	*85.85*	*79.63*
14	*72.56*	*80.54*	*34*	*79.35*	*80.69*
15	*72.79*	*78.03*	*35*	*72.01*	*71.31*
16	*74.87*	*79.98*	*36*	*85.56*	*74.74*
17	*85.51*	*83.75*	*37*	*76.65*	*78.30*
18	*81.42*	*82.26*	*38*	*80.23*	*80.72*
19	*80.91*	*74.52*	*39*	*83.56*	*81.90*
20	*76.81*	*80.68*	*40*	*76.19*	*75.05*

Table 1: Simulation test results of the system.

From the above experimental research, it can be seen that the target user recommendation system in English cloud classrooms based on cloud computing and behavior modeling proposed in this paper can effectively improve the quality of English online teaching.

5 CONCLUSIONS

In the English online teaching environment, learners who participate in the same course do not have the same motivation for learning. For example, learners with the goal of improving their professional skills typically spend more time studying course materials and completing coursework and projects. However, learners who aim to understand the content of the course mostly browse the course pages at will, and are less involved in answering coursework and quizzes. It can be seen that, driven by different learning motivations, the specific learning behaviors of learners will also be quite different.Moreover, even learners with the same learning motivation tend to exhibit different learning patterns due to differences in their preferences.This paper combines cloud computing technology to analyze student behavior in English cloud classroom teaching, and recognizes student behavior through behavior modeling. The experimental research shows that the target user recommendation system of English cloud classroom based on cloud computing and behavior modeling proposed in this paper can effectively improve the quality of English online teaching. The synergy of Collaborative CAD multimedia technology, cloud computing, and behavior modeling has reshaped the educational landscape. As we look to the future, we envision a continued commitment to refining recommendation algorithms, expanding the frontiers of 5G technology in education, and exploring new dimensions of behavior modeling.

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