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Construction of University Student Sports Activity Tendency Model Based on Fuzzy Optimization Algorithm

Wan Nan, Wan Lu
Jiangxi Science and Technology Normal University, Nanchang Jiangxi, 330013, China
Yuzhang Normal University, Nanchang Jiangxi, 330029, China

***Abstract*—In order to ensure that we can still get the maximum advantage in the information age, according to the actual situation of college sports activities, we propose the construction of college students' sports activities (The tendency model of College Students' sports activities, TMCSSA) based on systematic fuzzy optimization algorithm. The establishment of the conceptual model of task decomposition for the integration of college students' sports activity preference model can effectively analyze the single data after decomposing, including effective preprocessing and the arrangement of college students' sports activities. Finally, the effectiveness of the model is verified by simulation experiments.**

Keywords-College Student Sports Activities; Modular University Student Sports Activities; Artificial Intelligence College Students Sports Activities; System Fuzzy Optimization Algorithm;

I. INTRODUCTION

Physical activity in colleges and universities is an important part of implementing the "National Fitness Program." The majority of students are large participants in the "National Fitness Program". By actively guiding students to participate in sports activities, we can promote the implementation of the "National Fitness Program" [1-2]. However, the current status of university students' fitness activities is worrying, and a considerable number of students are reluctant to participate in sports activities [3]. In general sense, the construction of the tendency model of college students' sports activities refers to the knowledge or information that is transmitted. It can also be understood as the use of a certain carrier to transmit to a specific person at a specific time and in a specific state, so that scientific research, production, and other practical activities are encountered. The problems reached have been effectively solved and some information or knowledge required for problem solving has been met [4]. The information technology in modern society is developed rapidly, the data is carrying increasingly rich information, and its scale and speed are showing a rapid growth trend. And its existing mode has also undergone major changes compared to the past [5].

This paper proposes a model of university student's sports activity tendency model based on fuzzy optimization algorithm. First of all, it constructs a model of university students' sports activity tendency, and then carries out pre-processing of disassembled data. At the same time, it arranges sports activities for college students. Based on the basic needs of college students' physical activity tendency model and the basic characteristics of their information sources, the university students' sports activity tendency model is constructed from multiple angles.

II. TENDENCY MODEL OF COLLEGE STUDENTS' SPORTS ACTIVITIES

The tendency model of university students' sports activities is a programming model for processing information sets. It was first used in Internet data information processing. After the technology was proposed, it was popularized in many fields including machine learning and data analysis. The university student sports activity tendency model can abstract the data processing tasks, store all the data as a format $< \mathrm{key}, \mathrm{value} >$, and the system fuzzy optimization algorithm can choose the language that they are good at to get functions Map and functions Reduce. Figure 1 shows the task decomposition conceptual model.

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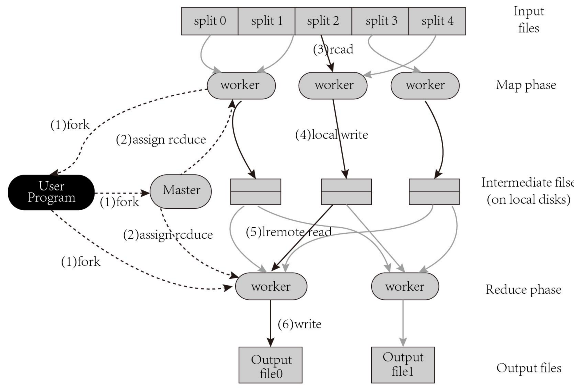

Figure 1. Tendency model of college students' sports activities

The integration of university students' sports activity preference model can decompose huge data sets and get small-scale single tasks. As a result, only a small amount of data information processing is needed for a single task, and the criteria are different based on the granularity of task division. The data set that needs to be processed may still exceed the level TB, and it may also cause problems such as inconsistent dimensions and abnormal scales. Therefore, the need for monomer pretreatment work is as follows:

① Non-dimensional processing of mission data

If there is more than one attribute index for the single task to be processed, then in order to ensure that each data can be added in order to eliminate the difference level between the different index dimensions, it needs to be dimensionless. The process is as follows:

a. $f_j,(j=1,2,\mathrm{L}\;,n)$ represents s_j decision-making indicators, a total of m plans, $a_i,(i=1,2,\mathrm{L}\;,m)$, and each plan and their indicators can cause the matrix $X=(x_{ij})_{m\times n}$, which is the decision matrix, $\overline{x}_j$ and s_j represents the sample mean and variance respectively.

② Distribution Measure Test of Task Data

The distribution measurement test can be performed based on the task data by the following steps, as follows:

a. Use the statistical population Ω to define the monomer task and determine the appropriate amount of data for the study sample $x_i,(i=1,2,\mathrm{L}\;,n)$.

b. Sort $x_i,(i=1,2,\mathrm{L}\;,n)$ in ascending order, denoted as $x_{(1)},x_{(2)},\mathrm{L}\;,x_{(n)}$.

c. Calculate $q_i=\Phi^{-1}\left[\frac{i-0.375}{n+0.25}\right],i=1,2,\mathrm{L}\;,n$. Inverse functions $\Phi^{-1}(x)$ belongs to the standard normal function. 0.375、0.25 are corrections.

d. Construct a Cartesian coordinate system with the horizontal axis representing the desired value and the vertical axis representing x_i .

③ Mission Data Outlier Processing

After the distribution measurement test, abnormal data may still exist, and the distribution of such data objects and data objects is inconsistent. Therefore, it is very important to analyze task data outliers and analyze whether the information they contain is valid or valuable. The specific process can be summarized as follows:

a. If the outliers appear in the task data, then on the one hand, the causes of the outliers can be analyzed through related technologies. If it is due to experimental techniques or because of human error, then no matter what the value is Whether it is an abnormal value or not must be discarded, that is, it is not counted.

b. If for some reason it is not possible to specify the technical reasons for the outliers, it is first necessary to conduct statistical tests to determine whether they should be retained or abandoned.

④Task Data Function Description

a.Smoothing random functions that are represented by X(t) in the interval range Γ can generally be regarded as a random process, with $t\in\Gamma$ representing time, and which can also be referred to as other variables outside of time. $X_1(t),\mathrm{L}\;,X_n(t)$ corresponds to represent n independent implementations of $X(t)$. The $y_i=(y_{i1},\mathrm{L}\;,y_{in})$ represents the observation data, n_i represents the number of observations for each i-curve. Therefore, the following formula can be used to represent the functional data characteristics:

$$y_{ij}=X_i(t_{ij})+\varepsilon_i(t_{ij}),i=1,2,\mathrm{L}\;,n,j=1,2,\mathrm{L}\;,n_i \tag{1}$$

b. Convergence of the smoothing technique on y_i to estimate its potential function form $X_i(t)$, $t\in\Gamma$ to obtain the corresponding value at any moment in the interval.

c. Analyze the observations value of the observation point $t_{ij}\left(j=1,2,\mathrm{L}\ ,n_i\right)$. If there is an error between the observation point $X_i\left(t_{ij}\right)$ and the point y_{ij} , then the function can be transformed by a smoothing process to obtain a function. Otherwise, if the two are identical at the observation point, that is, If there is no error at this time, the discrete data can be transformed into a function by interpolation.

⑤ Task Data Application Reanalysis

If the observations have been preprocessed, all the curves are obtained, $X_1\left(t\right),\mathrm{L}\ ,X_n\left(t\right)$, $t\in\Gamma$. The descriptive analysis can then be used to analyze the basic characteristics of data changes for in-depth analysis.

The descriptive analysis of data is mainly performed by means of the mean, variance, correlation coefficient, etc. The first two are the basis for the analysis of all function types. The following are the mean functions:

$$\overline{x}\left(t\right)=\frac{1}{n}\sum_{i=1}^{n}x_i\left(t\right),\forall t\in\Gamma \tag{2}$$

Similarly, the variance function reflects the variance of the function's stagnation point, as follows:

$$VarX\left(t\right)=\frac{1}{n-1}\sum_{i=1}^{n}\left[x_i\left(t\right)-\overline{x}\left(t\right)\right]^2,\forall t\in\Gamma \tag{3}$$

The covariance function is:

$$cos\,X\left(t_1,t_2\right)=\frac{1}{n-1}\sum_{i=1}^{n}\left[x_i\left(t_1\right)-\overline{x}\left(t_1\right)\right]\left[x_i\left(t_2\right)-\overline{x}\left(t_2\right)\right],\forall t_1,t_2\in\Gamma \tag{4}$$

Correspondingly, the relevant function is:

$$co\,rrX\left(t_1,t_2\right)=\frac{cov\,X\left(t_1,t_2\right)}{\sqrt{VarX\left(t_1\right)VarX\left(t_1\right)}},\forall t_1,t_2\in\Gamma \tag{5}$$

The mutual covariance function mainly analyzes the level of covariance that two random functions have at different time points. As follows:

$$cov\,X,Y\left(t_1,t_2\right)=\frac{1}{n-1}\sum_{i=1}^{n}\left[x_i\left(t_1\right)-\overline{x}\left(t_1\right)\right]\left[y_i\left(t_2\right)-\overline{y}\left(t_2\right)\right],\forall t_1,t_2\in\Gamma \tag{6}$$

Correspondingly, the cross-correlation function is:

$$co\,rrX,Y\left(t_1,t_2\right)=\frac{cov\,X,Y\left(t_1,t_2\right)}{\sqrt{VarX\left(t_1\right)VarY\left(t_2\right)}},\forall t_1,t_2\in\Gamma \tag{7}$$

It should be clear that the symmetry is no longer in the cross-correlation function, that is to say:

$$co\,rrX,Y\left(t_1,t_2\right)=co\,rrY,X\left(t_1,t_2\right)\neq cov\,X,Y\left(t_2,t_1\right),\forall t_1,t_2\in\Gamma \tag{8}$$

III. Experiments and Analysis

In this article, students from a certain area are studied, and a total of 2,940,942 records of various performance data are obtained, with a data volume of 0.4 PB. The performance data includes structured data such as art design recognition and college student sports activity time in the form of numerical values. After pre-processing the date, we finally obtained a distribution trend chart of system fuzzy optimization algorithm about university student sports activity, as shown in Figure 2.

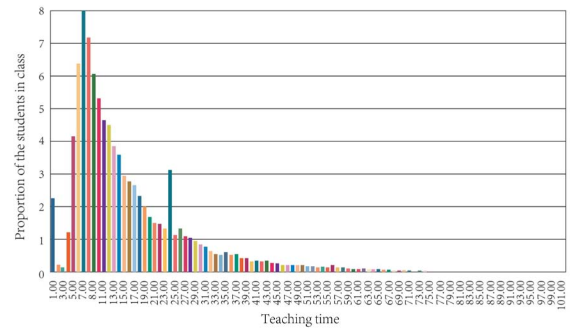

Figure 2. System fuzzy optimization algorithm test of college students' sports activity

In order to further verify the validity of the construction of the TMCSSA model in this paper, the following contrasts with the traditional university student sports activity model are conducted. Assuming that the total number of sports activities for college students is Q , there is a corresponding sample (k times d dimension) for any college student sports activity.

Assuming that there are Q college sports activities and each college student sports activity has k times d-dimensional samples, the (flops) bound of the TMCSSA model is $O\left(dkQ+dQ\right)=O\left(dkQ\right)$. Here, the training sample we use is the flow of college students' physical activity. If a new sample appears, it needs to be retrained. When the number of samples is N , the bound of the total floating-point operand can be expressed as follows:

$$O\left(\sum_{k-2}^{N}dkQ\right)=O\left(dQN^2\right) \tag{9}$$

The corresponding storage cost bound is expressed by the following formula:

$$O\left(dQN\right) \tag{10}$$

The difference is that the worst time complexity of any iteration of the traditional university student sports activity model and the TMCSSA model of this paper is $O\left(dQ\right)$.

For any sample whose number is N , the total floating-point operand is represented by the following formula:

$$O(dQN) \tag{11}$$

The corresponding storage cost bound is expressed by the following formula:

$$O(dQ) \tag{12}$$

Comparing equations (9), (10), and (11), (12), the construction and analysis of the TMCSSA model in this paper is reduced by a quantitative level compared with the construction and analysis of other models. There is a certain relationship between the running time of the model and the number of training samples.

In Figure 3, the traditional university student sports activity model and the TMCSSA model of this article are compared and analyzed. yeast, letters, digits and four college students' sports activities are taken as the basic objects, which subjected to 10 random experiments to obtain the average effective time. We can observe Figure 2 and we can see that the sports activities of the four college students in the TMCSSA model are much less time-consuming than the traditional college students' physical activity model, which proves the validity of the model construction and analysis of the TMCSSA model.

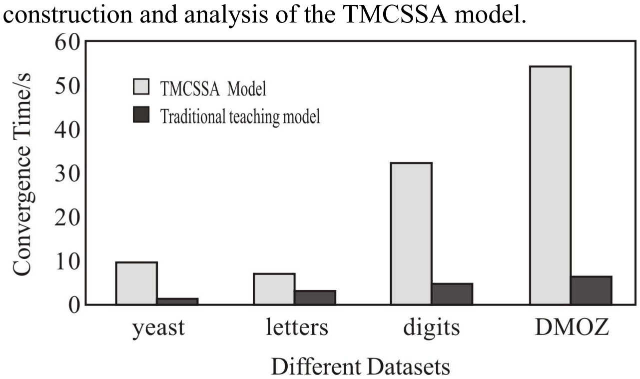

Figure 3. Comparison of the effective time of TMCSSA model and traditional sports activity model in this paper.

In order to further analyze the validity of the construction and analysis methods of the two models, in Figure 2 again, aiming at the sports activities of yeast college students, the target value iteration curves of the two analysis methods are plotted. We observed and analyzed Figure 4 and found that in the TMCSSA model of this paper, it only takes only 30 times, and it tends to be a stable value. However, in the traditional university student sports activity model, it needs 120 times.

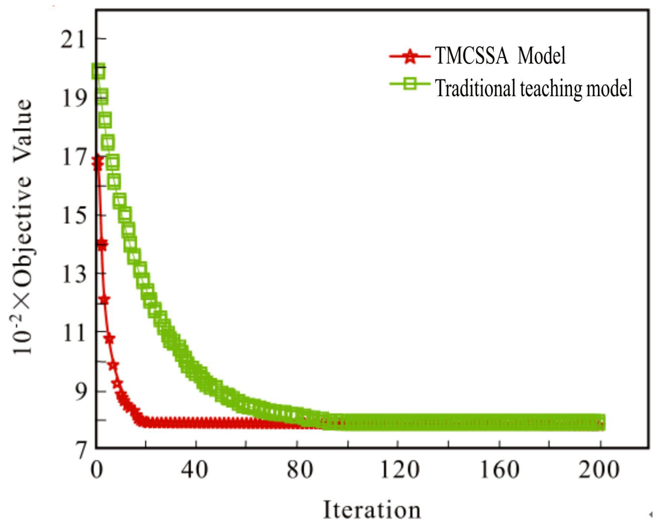

Figure 4. Comparison of the effectiveness of TMCSSA model and traditional sports activity model on yeast.

IV. Conclusions

This paper highly combines the system fuzzy optimization algorithm with the TMCSSA model. It not only clarifies the construction of the model, but also attempts to apply the system fuzzy optimization algorithm to the sports activities of college students in the information age. The model will be further advanced with the development of the information age, which also allow the system's fuzzy optimization algorithm and TMCSSA model to be continuously improved.

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