Acta Technica 62 (2017), No. 7A, 1547–1560

Construction of physical education assessment system based on soft fuzzy rough set

Junwei Yang[1]

Abstract. A method for construction of physical education assessment system based on data mining is proposed in this Article to improve effectiveness of the physical education assessment system constructed. Objectives on training program description for physical education assessment system are given. A soft fuzzy rough set is used for reference to solve uncertainty and applied in classification for construction of physical education assessment system. And a set of feature words is expressed in the form of vector space model for further data structurization. At meantime, based on Rough Set Theory, a soft fuzzy rough set model is applied and improved to be capable in solving problems regarding construction of physical education assessment system. And such model is used for classification of the physical education assessment system to get a set of classified assessment system of each test sample data. The results of test and comparison show that, the method proposed herein is capable of completely eradicating the setting of certain elective courses being identical to required courses and promoting diverse development of students.

Key words. Soft fuzzy, Rough set, Physical education assessment system, Assessment system
.

1. Introduction

As blueprint design to turn educational concepts to specific teaching behavior, Professional Training Program is a teaching instruction document on integrated design and planning for student training according to national requirements on training of talents in colleges and universities, as well as main basis organization and management of professional teaching activities. While Post-Olympic Era and Opinions on Speeding up the Development of Sports Industry to Promote Sports Consumption upgrade National Fitness to national strategy, the big market of sports, recreation and fitness, and the football, snow and ice sports and outdoor exercise to be given priority as determined during the 13th Five-Year Plan of Sports Industry also imposed

[1]Department of sports and art, BengBu Medical College, AnHui Province, 233000, China

new demands for sports colleges on talent training. Under such circumstances, how those sports colleges resolve actual conflicts in talent training by effective amendment to training program, how they reflect specialty running characteristic, respond to social demand changes and bear their cultural deposit, have become an urgent.

Training objective is the prerequisite for professional training, with index and orientation. Only determination of specific and scientific training objective can lead the talent training develop correctly. It can be concluded from construction of Conformity Assessment Program (RFC) issued by Ministry of Education that, the running orientation of new undergraduate schools shall be evidenced by locality, education and application, offering comprehensive training with knowledge, ability and quality requirements. The Course Scheme issued by Ministry of Education has provided specifications on talent training comprehensively and systematically. It not only involves moral education, basic quality and literacy, research ability, physique, health habits and healthy lifestyles, but also imposes requirements on innovation, self-learning ability, social adaptability, foreign language and computer, aesthetic appreciation and creativity. The results of comparison and analysis on training specifications in physical education professional training programs from six schools show that, contents of such programs essentially comply with the requirements on talent training specifications under Course Scheme issued by Ministry of Education. But those schools also provide difference specific requirements according to their own characteristics. (1) For expression of political thoughts, those requirements cover having ardent love for the motherland, understanding and mastering basic principles of Marxism-Leninism, Mao Zedong Thought, Deng Xiaoping Theory and the Three Represents theory, to establish correct views on world, on life and values. Get familiar with national principles, policies and regulations on education and sports. Have good moral and professional ethics, cherish posts and devote wholeheartedly to work, observe disciplines and abide by laws, and work together. Have innovative and strong practical ability. Those schools can express above aspects in different ways, each of which has certain similarity. (2) For requirements on professional knowledge, professional ability and quality, all training objectives of such schools reflect the requirements on profound and solid professional knowledge, rich educational and scientific knowledge, and extensive basic knowledge of culture and science which students in physical education shall have. Although expressed with characteristics specifically, connotation is substantially the same.

The construction of physical education assessment system based on soft fuzzy rough set proposed in this Article involves two aspects. One is promotion of algorithm performance and another is assessment of algorithm efficiency. The problem model of physical education assessment system is studied to propose the optimization objective function and constrains for problems in physical education assessment system, to build a mathematical optimization model and to give multi-objective weight adaptive form. At meantime, soft fuzzy rough set algorithm is introduced for solution of strategic benefit model in physical education assessment system and to improve assessment performance of the algorithm.

2. Problem model of physical education assessment system

2.1. Problem model

Assume under implementation of the physical education assessment system, there are substitute PE G teachers, C classes to be assessed, L courses, T time periods for physical education assessment system and R sites, its mathematical model is described as:

The set of classes assessed is expressed as $C = \{c_1, \cdots, c_C\}$. The set of each class population is expressed as $K = \{k_1, \cdots, k_C\}$. The set of substitute teachers is expressed as $G = \{g_1, \cdots g_G\}$, the set of course numbers which the teachers are responsible for is expressed as $Y = \{y_1, \cdots y_G\}$. The set of PE courses is expressed as $L = \{l_1, \cdots l_L\}$ and the quantity of classes opened for each course is expressed as $Z = \{z_1, \cdots z_L\}$. The set of course sites is expressed as $R = \{r_1, \cdots, r_R\}$. And quantity of students hold by each teacher is expressed as $X = \{x_1, \cdots, x_R\}$. The set of each time period is expressed as $T = \{t_1, \cdots, t_T\}$.

Through calculation of Cartesian product on time and site, the problems in physical education assessment system are converted into model pairwise of course and suitable time and site, in the form of:

$$M = T \cdot R = \{(t_1, r_1), \cdots, (t_T, r_R)\} . \tag{1}$$

2.2. Model constraint

Constraint 1: No more than one course shall be offered to the same class at the same time, namely the constraint form shall be:

$$\sum_{g=1}^{G} \sum_{l=1}^{L} \sum_{r=1}^{R} c_c g_g l_l r_r t_t \leq 1 . \tag{2}$$

In which, $c = 1, 2, \cdots, C$, $t = 1, 2, \cdots, T$. If in site r_r and at time t_t, class c_c is taken by substitute teacher g_g for teaching of course l_l, the expression is $c_c g_g l_l r_r t_t = 1$, otherwise it shall be 0.

Constraint 2: No more than one course shall be offered by the same teacher at the same time, namely the constraint form shall be:

$$\sum_{c=1}^{C} \sum_{l=1}^{L} \sum_{r=1}^{R} c_c g_g l_l r_r t_t \leq 1 . \tag{3}$$

In which, $g = 1, 2, \cdots, G$, $t = 1, 2, \cdots, T$. If the teacher g_g teaches course l_l for class c_c only in site r_r and at time t_t, the expression is $c_c g_g l_l r_r t_t = 1$, otherwise it shall be 0.

Constraint 3: No more than one course shall be offered in the same site at the same time, namely the constraint form shall be:

$$\sum_{c=1}^{C}\sum_{g=1}^{G}\sum_{l=1}^{L} c_c g_g l_l r_r t_t \leq 1\,. \tag{4}$$

In which, $r = 1, 2, \cdots, R$, $t = 1, 2, \cdots, T$. If the site r_r is used by teacher g_g for teaching course l_l to class c_c at time t_t only, the expression is $c_c g_g l_l r_r t_t = 1$, otherwise it shall be 0.

2.3. Optimization objective

The physical education assessment system is substantially a problem of multi-objective optimization, with optimization objectives as follows:

Objective 1: Important courses are arranged at time periods with good teaching effect. If $a_i\,(i = 1, 2, 3, 4, 5)$ means the 5 teaching sessions each day, according to actual teaching experience, sessions 1, 3 and 5 have best teaching effect, which is expressed as $a_i = 1\,(i = 1, 3, 5)$. And sessions 2 and 4 have worse teaching effect, which is expressed as $a_i = 0\,(i = 2, 4)$. Apply parameter $\beta_j = 1\,(j = 1, 2, 3, 4)$ to present course significance, such as granting different weight values to selective courses, basic courses, major courses and degree courses, the optimization objective is:

$$\max\left(f_1\right) = \sum\left(a_i\beta_j\right). \tag{5}$$

Objective 2: Consider the teaching time and site proposed by teachers, assume title coefficient $\chi_i\,(i = 1, 2, 3, 4)$, referring to teaching assistant, lecturer, associate professor and professor. The willing of teachers while setting teaching time can be expressed as $\delta_i = 0, 1, 2$, which refers to no, ok and willing respectively. Such optimization objective is expressed as:

$$\max\left(f_2\right) = \sum\left(\chi_i\delta_j\right). \tag{6}$$

Objective 3: Courses with more periods each week (such as $n \geq 4$) shall be arranged every other day as much as possible to ensure teaching effect. The definition $\beta_j = 1\,(j = 1, 2, 3, 4)$ is identical to Objective 1, and the definition $\varepsilon_i\,(i = 1, 2, 3, 4)$ refers to the teaching effect when courses are arranged every i days, then optimization objective is expressed as:

$$\max\left(f_3\right) = \sum\left(\beta_i\varepsilon_j\right). \tag{7}$$

Objective 4: objective of resource utilization, the greater than ratio of maximum capacity in the site occupied by student number k_c, the higher the utilization will be, with optimization objective expressed as:

$$\max\left(f_4\right) = \sum\left(k_c/r_r\right). \tag{8}$$

In objective functions above, problems in application of multi-objective function are that, optimization objectives are too excessive, final optimization scheme is unclear and the scheme is not the best. Problems in application of individual-objective function are that each objective has different values. Conventional scheme applied weight method for integration but the weight selection requires knowledge. In process of actual optimization, each objective weight changes at real time, making weight fixing obviously unsuitable. Therefore, an adaptive weight form is proposed as follows:

$$f = \max\left(\sum_{m=1}^{4} \frac{f_m - f_m^{\min}}{f_m^{\max} - f_m^{\min}}\right). \tag{9}$$

In which, f_m is the current individual adaptive value of the m generation of group, $f_m^{\max}$ is the maximum adaptive value of such generation of group, and $f_m^{\min}$ is the minimum adaptive value. In this way, weight adaptive form can be achieved and searching accuracy can be improved.

3. Soft fuzzy rough set model

3.1. Soft fuzzy rough set

Soft Fuzzy Rough Set theory introduces the concept of soft threshold selection in soft margin SVM and proposes a concept of soft distance, which is different from the original method in calculating the minimum distance of samples [8].

Definition 1: Give a physical sample x and a physical sample set $Y = \{y_1, y_2, ..., y_n\}$, the soft distance between x and Y is defined as:

$$SD(x, Y) = \arg\max_i \{d(x, y_i) - C \times m_i\}, y_i \in Y, i = 1, 2, \ldots, n, \tag{10}$$

In which, $d(x, y_j)$ is distance function between x and y_j, C is penalty factor and m_i is the number of samples meeting with conditions $d(x, y_j) < d(x, y_i), j = 1, 2, ..., n$.

Figure 1 gives an example to determine soft distance. Assume sample x belongs to class1 and other samples belong to Class 2, express the sample set with Y. If we take $y1$ as a noise sample and ignore it, *SD(x, Y)*shall be $d2$. Therefore a penalty item is needed to determine how much noise samples shall be ignored. If one sample is ignored, *d(x,yj)* will reduce C. For all candidate distances *d(x,yj)*, assume $d(x, y_k) = \arg\max_i \{d(x, y_i) - C \times m_i\}$ as soft distance between x and Y.

In other words, distance *d'(x,yj)* is the maximum value after punishing all ignored samples. Please refer to Section 4.3 for selection of parameter C.

Based on soft distance, the soft fuzzy rough set is defined as:

Definition 2: Take U as a non-empty domain, R as a fuzzy equivalence relation on it, and F(U) is the fuzzy power set of U. The lower and upper approximation of

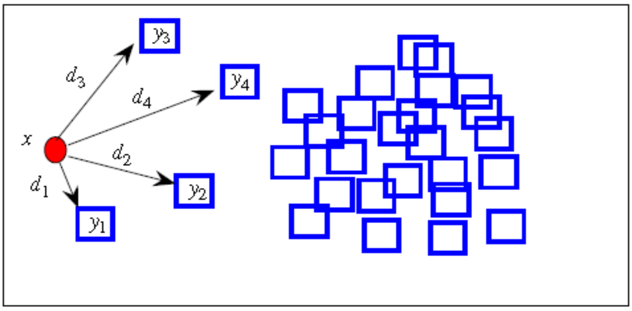

Fig. 1. Diagram of soft distance

soft fuzzy in F∈F(U) is defined as:

$$\begin{cases} \underline{R}^S F(x) = 1 - R\left(x, \arg_y \sup_{F(y)\le F(y_L)} \{1 - R(x,y) - C \times m\}\right), \\ \overline{R}^S F(x) = R\left(x, \arg_y \sup_{F(y)\ge F(y_U)} \{1 - R(x,y) + C \times n\}\right). \end{cases} \tag{11}$$

In which:

$$\begin{cases} y_L = \arg_y \inf_{y\in U} \max\{1 - R(x,y), F(y)\}, \\ y_U = \arg_y \sup_{y\in U} \min\{R(x,y), F(y)\}. \end{cases} \tag{12}$$

C is a penalty factor, m is the number of samples ignored when calculating $\underline{R}^S F(x)$ and n is the number of samples ignored when calculating $\overline{R}^S F(x)$.

If set A is clear, the membership degree of sample x in A with approximation under soft fuzzy is expressed as:

$$\underline{R}^S A(x) = 1 - R(x, y_{AL}). \tag{13}$$

In which,

$$\begin{aligned} y_{AL} &= \arg_y \sup_{A(y)=0} \{1 - R(x,y) - C \times m\} \\ &= \arg_y \sup_{A(y)=0} \{d(x,y) - C \times m\} = \arg_y SD(x, U - A). \end{aligned} \tag{14}$$

Obviously, $\underline{R}^S A(x)$ is equal to the soft distance from sample x to $U - A$.

3.2. Soft fuzzy rough classifier

Based on definition of approximation under soft fuzzy mentioned above, Hu Qinghua et al designed a stable classifier [8]. It can be used to solve problems of individual assessment system classification.

Principles of it are summarized as: calculating the value of approximate membership degree of a sample to be classified under soft fuzzy of each class. Give a training sample set with k classes and a sample x to be classified. Firstly, assume x belongs to each class, calculate the value of approximate membership degree of sample x under soft fuzzy of class k. Then divide x into the class with maximum membership degree, which is expressed as:

$$class_i(x) = \arg \max_{1 \le j \le k} \{\underline{R}^S class_j(x)\}. \tag{15}$$

In which, $\underline{R}^S class_i(x)$ is the approximate membership degree of sample x under soft fuzzy of class $class_i$.

The algorithm is described as follows:

Input: training sample set $X = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, testing sample set $X' = x'_1, x'_2, ..., x'_m$;

Output: class *classi* of each testing sample *xi*.

Step 1: calculate the number of classes;

Step 2: process each testing sample *xi'*$\in X'$ as follows:

For each class *classj*∈Y(Y={y1,y2,...,yk}), calculate the distance between *xi'* and each sample in different classes to get candidate distance.

Sort the candidate distances obtained and calculate the corresponding soft distance of class *classj* according to Formula (3).

It can be seen from Formula (6)-(7) that, the value of soft distance between *xi'* and sample in different classes obtained in Formula (1) is equal to that of the lower approximate membership degree. So we can get the approximate membership degree of sample *xi'* under soft fuzzy of each class.

Select corresponding class assessment system *classt* in case of maximum membership degree and return it, obtain the class of sample *xi'*.

Step 3: Repeat step 2 until get class assessment system of each testing sample.

3.3. Parameter Settings

It can be seen from Figure 1 in Section 4.1 that, the value of penalty factor C in soft fuzzy rough set is significant to its stability. For parameter settings, a method is given in Reference [8].

Assume that, take sample x as example, give the degree of belief f of the soft hypersphere with such sample as center. During calculating the degree of belief of such soft hypersphere, if the value is greater than or equal to f, when belief degree equals to f, the value of ratio between radius difference of soft and hard hypersphere, with the number of few samples in different classes from upper soft hypersphere is the value of C, taking sample x as center. At meantime, the belief degree of approximation under soft fuzzy can be assured. For a data set containing samples, take the average of C calculated by taking each sample as center, value of parameter C under such data set can be obtained.

For data set of physical education assessment system construction proposed herein, parameters in each class are selected by converting data of physical education assessment system construction into various binary data sets. For different classes, BR method may lead to different parameter values, which can be concluded from Formula (9). The weighted average of each parameter selected by SFRC modified algorithm is considered as the value of its penalty factor C. the weight value is the weight of the number of assessment system from each class, in all assessment systems, which can be concluded from Formula (10).

The Formula to calculate parameter C is as follows:

$$C_i = \frac{SD(x,Y) - HD(x,Y)}{m}\,. \tag{16}$$

$$C = \sum_{i=1}^{L} w_i \times C_i\,. \tag{17}$$

In which, L is the total number of assessment system and wi is the weight value of class i. The approximate belief degree under soft fuzzy selected in testing under the Article is greater than or equal to 95%, namely the sample error rate in soft hypersphere is less than 5%.

4. Building of classification model for physical education assessment system construction

4.1. Learning construction of physical education assessment system

Most of current classification studies are focusing on individual assessment system data. However, in certain actual applications, one training sample can always attribute to multiple classes, namely the set of one assessment system $Y \subseteq L$. Such data is called the data for construction of physical education assessment system (multi-label).

Assume D is a data set for physical education assessment system construction and contains $|D|$ samples. $X = \{x_1, x_2, ..., x_n\}$. And $L = \{y_1, y_2, ..., y_m\}$ refers to training sample set, refers to the set of class assessment system which samples in such set belong to. In which, n is the total number of training samples, m is the total number of assessment systems, then data set D can be expressed as: $\{(x_1, Y_1), (x_2, Y_2), ..., (x_n, Y_n)\}$. In which $xi \in X$, $Y_j \subseteq L$, xi is the sample for physical education assessment system construction and Yj is the set of the corresponding class assessment system of the sample. Detailed descriptions of data set for physical education assessment system construction have been given in Reference [16].

4.2. Building of classification model for physical education assessment system construction based on problem conversion

The main idea for method of problem conversion classification is that, each sample *(xi, Yi)* for physical education assessment system construction is processed into data *(xi,yi)* containing $|Yi|$ individual assessment systems. In which, $yi \in Yi$, and the existing classification model is used for classification of the data set of individual assessment systems converted to obtain the set of assessment system in each testing sample.

Binary relevance (BR) method is used in this Article for data conversion. It trains binary $|L|$ classifiers, each of which divides one class in L only, and $|L|$ refers to total number of class assessment systems. It converts the original data set for physical education assessment system construction into $|L|$ data sets Dp of individual assessment system only with two classes. If the class assessment system set Yi of data sample Dxi in the individual assessment system converted contains yi, it will be expressed as 1, otherwise as 0. For a sample physical education assessment system construction, the assessment system in the set output by BR method is composed by $|L|$ class assessment systems with assessment system as "1" in base classifier output.

After conversion of processed data for physical education assessment system construction, training and learning of various binary classifiers according to the individual assessment system classification algorithm given in Section 4.2, a classifier for physical education assessment system construction based on soft fuzzy rough set model is formed.

4.3. Building of classification model for physical education assessment system construction based on algorithm adaptation

The main idea for method of algorithm adaptation classification is that improve the existing algorithm to have capability in directly processing data for physical education assessment system construction, and give results in the form of class assessment system set. Assessment system in such set is the class where the sample belongs to. In this Article, the existing soft fuzzy rough set model to process individual assessment system data is transformed and used in classification for physical education assessment system construction.

For existing soft fuzzy rough set model, the approximate membership degree of its sample under soft fuzzy is determined according to the soft distance between samples to be classified and samples in different classes. As the same with principles in soft fuzzy rough classifier, a value of approximate membership degree of sample to be classified relative to each class under soft fuzzy needs to be calculated.

Assume there are $|L|$ class assessment systems in the data set for physical education assessment system construction, sample xi is the sample to be classified, Yi is the set of class assessment system which such sample belongs to. The process to obtain assessment system set of xi is as follows:

Step1: Input a data set for physical education assessment system construction and process the expression form of its class assessment system, to the extent that, in each class assessment system, "1"means the sample belongs to the class and "0" means not.

Step2: Assume sample xi for physical education assessment system construction belongs to each class and according to calculations of approximate membership degree under soft fuzzy, obtain the value of lower approximate membership degree of $|L|$ samples xi in each class. Such membership degree is the measurement of significance on membership of sample xi in each class.

Step 3: give a limit and divide the classes that have higher contribution to sample xi.

Step 4: Output set of such classes, which is the class assessment system set Yi of sample xi.

Step 5: For each sample repeat Step 2-4, obtain set of class assessment system for all samples.

The Formula is expressed as follows:

$$labelset_i(x) = \underset{class_i}{\arg} \left\{ \underline{R}^S class_i(x) | \underline{R}^S class_i(x) \geq T(x) \right\}. \tag{18}$$

In which $T(x)$ means membership degree limit of sample x.

For selection of such limits, two methods are given. One is to give a fixed threshold. Express class relevance with μ, and express each converted value of membership degree with μ, where $0 \leq \mu \leq 1$. Firstly, assume the relevance of maximum membership degree is 1, the ratio of membership degree of all other classes and such maximum value is relevance of each class. Then assume a threshold (for example 90%), for any value greater than such threshold, the sample is determined to belong to relevant class, with relevant assessment system set locating at "1", otherwise at "0". Consider particularity of each sample, overall threshold selection may not be applicable to certain samples. Therefore, another method for threshold selection considering particularity of each sample is given. Directly take the expected value Mi of lower approximate membership degree of $|L|$ samples, which is used as limit for class determination. If the value of lower approximate membership degree of one sample under class yj is greater than Mi, the sample is determined to belong to class Mi, otherwise not.

5. Test and Analysis

Test objects are selected from objects in PE Class Schedule of a university in China, with elements in physical education assessment system shown in Table 1. The physical education assessment system developed is achieved based on visual c++.

Table 1. Elements of physical education assessment system

Elements	Students	Teachers	Classes	Courses	Sites	Tasks
Quantity	6200	387	125	669	168	669

Algorithm in Reference [5] is taken in this Test as contrast algorithm, objective function value and evolution time are used as assessment indicators. The Test was carried out for 20 times. Comparison on effect of physical education assessment system is outlined in Table 2.

Table 2. Comparison on effect of physical eduction assessment system

Method	Number of Days in Each Week for Main Courses	Interval of Same Course Teaching	Average Number of Sessions each Day
Reference [5]	2.3	1.3	6.3
This Article	2.7	1,5	4.8
Site Utilization (%)	Number of Courses Missed	Teacher Satisfaction	Conflict Rate of Physical Education Assessment System (%)
89.5	18	86.4	16.3
99.3	0	99.5	1.2

Table 2 gives comparison on effect of algorithm proposed herein and algorithms in References [5] and [7] in physical education assessment system. From which we can see that indicators of algorithm proposed herein, including site resource utilization, number of course missed, site satisfaction, conflict rate of physical education assessment system are obviously superior to the physical education assessment system method mentioned in References [5] and [7]. The effectiveness of algorithm proposed herein in application of physical education assessment system is also be verified. Results of optimal solution among the three contrast methods are outlined in Table 3.

Table 3. Optimal solution of each algorithm

Algorithm	Reference[5]	Reference[7]	Algorithm Herein
1	0.165	0.155	0.161
2	0.123	0.144	0.140
3	0.052	0.142	0.131
4	0.065	0.039	0.049
5	0.121	0.143	0.098
6	0.194	0.027	0.062
7	0.007	0.117	0.122
8	0.065	0.031	0.046
9	0.140	0.011	0.017
10	0.060	0.184	0.169
Optimal Solution	-0.241	-0.273	-0.293

It can be seen from results shown in Table 3 that, under the same setting constraint, algorithm proposed herein has relatively better benefit on physical education assessment system. The program for physical education assessment system is more reasonable and satisfaction on such assessment system is higher. The test results above show that, algorithm proposed herein is efficient in solution process to the combination analysis model of physical education assessment system and has better performance.

On this basis, the unified setting and selective by students themselves in Major Selective Course Program 2007 was reformed. Each major is designed with 2-3 modules reflecting major development direction or different professional skills, offering students with the space of self-selection while avoiding the problem of man-specific course setting caused by common issues in sports schools, such as narrow professional background and lack of faculty. It can been seen from Table 4 that, Training Program proposed herein not only improves the specially selection space by averagely 3%, but also completely eradicates the stubborn problems such as setting of certain elective courses being identical to required courses, making it impossible for diverse development of students.

Table 4. Comparison of elective courses for training programs

Major	Training Program 2007			Training Program Herein		
	Score R equired	Selection Range	Specially Selection Space	Score Required	Selection Range	Specially Selection Space
Physical Education	14	34	2.42	14	50.2	3.62
Athletic Training	24	41	1.71	16	52	3.21
Martial Arts And Traditional Ethnic Sports	8	14.5	1.82	18	27	1.50
Dance Performance	16	23.6	1.47	16	30.2	1.91
Social Sports Guidance And Management	39.5	69.6	1.75	29	69	2.34
Sports Human Science	28	32	1.13	29	54	1.93
Applied Psychology	24	30	1.24	34	47.3	1.35
Sports Rehabilitation	34	41.2	1.23	21	44	2.04
Utility Management	27	27	1.01	32	42	1.28
Sports Economy And Management	30	30	1.02	21	41	2.04
Journalism	25	40	1.55	23	41	1.85
English	12	27	2.24	21	40	2.01
Leisure Sports	14	26	51	8	38	2.05

6. Conclusions

A method for construction of physical education assessment system based on data mining is proposed and objectives on training program description for physical education assessment system are given in this Article. A soft fuzzy rough set is used herein for reference to solve uncertainty and applied in classification for construction of physical education assessment system. At meantime, based on Rough Set Theory, a soft fuzzy rough set model is applied and improved to be capable of solving problems regarding construction of physical education assessment system. And such model is used for classification of the physical education assessment system to get a set of classified assessment system of each test sample data. The results of test and comparison show effectiveness of the method proposed herein.

References

[1] L. R. Stephygraph, N. Arunkumar: *Brain-actuated wireless mobile robot control through an adaptive human-machine interface.* Advances in Intelligent Systems and Computing *397* (2016), 537–549.

[2] Z. Lv, A. Halawani, S. Feng, H. Li, S. U. Réhman: *Multimodal hand and foot gesture interaction for handheld devices.* ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) *11* (2014), No. 1s, 10.

[3] Y. Z. Chen, F. J. Tang, Y. Bao, Y. Tang, G. Chen: *A Fe-C coated long period fiber grating sensor for corrosion induced mass loss measurement.* Optics letters *41* (2016), 2306–2309.

[4] N. Arunkumar, S. Jayalalitha, S. Dinesh, A. Venugopal, D. Sekar: *Sample entropy based ayurvedic pulse diagnosis for diabetics.* IEEE-International Conference on Advances in Engineering, Science and Management, ICAESM-2012, art. no. 6215973 (2012) , 61–62.

[5] Y. J. Zhao, Y. H. Hu, J. J. Liu: *Random Triggering-Based Sub-Nyquist Sampling System for Sparse Multiband Signal.* IEEE Transactions on Instrumentation and Measurement. *66* (2017), No. 7, 1789–1797.

[6] X. Du, L. Chen, D. Huang, Z. Peng, C. Zhao, Y. Zhang, Y. Zhu, Z. Wang, X. Li, G. Liu: *Elevated Apoptosis in the Liver of Dairy Cows with Ketosis.* Cellular Physiology & Biochemistry *43* (2017b), No. 2, 568–578.

[7] N. Arunkumar, K. K. Ram, V. Venkataraman: *Automatic detection of epileptic seizures using permutation entropy, Tsallis entropy and Kolmogorov complexity.* Journal of Medical Imaging and Health Informatics *6* (2016), No. 2, 526–531.

[8] Y. Y. Zhang, A.,Algburi, N. Wang, V. Kholodovych, D. O. Oh, M. Chikindas, and K. E.. Uhrich: *Self-assembled Cationic Amphiphiles as Antimicrobial Peptides Mimics: Role of Hydrophobicity, Linkage Type, and Assembly State*, Nanomedicine: Nanotechnology, Biology and Medicine *13* (2017), No. 2, 343–352.

[9] Y. Song, N. Li, J. Gu, S. Fu, Z. Peng, C. Zhao, Y. Zhang, X. Li, Z. Wang, X. Li: *β-Hydroxybutyrate induces bovine hepatocyte apoptosis via an ROS-p38 signaling pathway.* Journal of Dairy Science *99* (2016), No. 11, 9184–9198.

[10] N. Arunkumar, K. R. Kumar, V. Venkataraman: *Automatic detection of epileptic seizures using new entropy measures.* Journal of Medical Imaging and Health Informatics *6* (2016), No. 3, 724–730.

[11] R. Hamza, K. Muhammad, N. Arunkumar, G. R. González: *Hash based Encryption for Keyframes of Diagnostic Hysteroscopy*, IEEE Access, https: //doi.org/10.1109/ACCESS.2017.2762405 (2017).

[12] J. W. Chan, Y. Y. Zhang, and K. E. Uhrich: *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry *26* (2015), No. 7, 1359–1369.

[13] Y. J. Zhao, L. Wang, H. J. Wang, and C. J. Liu: *Minimum Rate Sampling and Spectrum Blind Reconstruction in Random Equivalent Sampling.* Circuits Systems and Signal Processing *34* (2015), No. 8, 2667–2680.

[14] S. L. Fernandes, V. P. Gurupur, N. R. Sunder, N. Arunkumar, S. Kadry: *A novel nonintrusive decision support approach for heart rate measurement.* Pattern Recognition Letters. https: //doi.org/10.1016/j.patrec.2017.07.002 (2017).

[15] N. Arunkumar, K. Ramkumar, V. Venkatraman, E. Abdulhay, S. L. Fernandes, S. Kadry, S. Segal: *Classification of focal and nonfocal EEG using entropies.* Pattern Recognition Letters *94* (2017), 112–117.

Received May 7, 2017