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Research on sensory comfort of tight-fitting sportswear based on intelligent models

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Abstract

In order to study the influence of human body parts on the overall comfort under different sports conditions, this paper designed a series of actions such as standing, squatting, running, walking, and so on, and obtained the key parts that affected the overall comfort at every experimental stage (i.e. every motion state) through subjective evaluation. That is, to study and analyze the comfort evaluation of every part and the whole body under different motions conditions, as well as the main parts that affect the overall comfort. In this paper, Analytic Hierarchy Process-Entropy weight, Fuzzy-Rough Set Theory, Analytic Hierarchy Process-Structural Equation Model, and Particle Swarm Optimization-Cuckoo Search were used to optimize the position index. At last, the prediction model of overall comfort was established by Adaptive Network-based Fuzzy Influence System. The input parameters are body part indexes screened by Analytic Hierarchy Process-Entropy weight, Fuzzy-Rough Set Theory, Analytic Hierarchy Process-Structural Equation Model and Particle Swarm Optimization-Cuckoo Search, respectively. And the output is the overall comfort evaluation value. Compared with the real value of overall comfort in every experimental stage, the effectiveness of Analytic Hierarchy Process-Entropy weight, Fuzzy-Rough Set Theory, Analytic Hierarchy Process-Structural Equation Model, and Particle Swarm Optimization-Cuckoo Search optimizing indexes is verified. The results show that: (1) About index optimization models, Particle Swarm Optimization-Cuckoo Search and Analytic Hierarchy Process-Entropy weight are better than Fuzzy-Rough Set Theory, so both Particle Swarm Optimization-Cuckoo Search and Analytic Hierarchy Process-Entropy weight could optimize index predicting overall comfort. (2) Different movements have great differences in the parts that affect the overall comfort.

Keywords

Tight-fitting sportswear, overall comfort, local comfort, prediction model, subjective evaluation

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Introduction

The comfort evaluation of sportswear has always been a hotspot in the study of clothing comfort. It is a result of the harmonious interaction between human physiological and psychological factors and sportswear under motion conditions. However, the research on the comfort of sportswear mainly focuses on the analysis of the physical and basic

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properties of clothing fabric, clothing esthetics, environment conditions, and other objective factors. With the in-depth study of the relationship between clothing and human beings, the research on wearable comfort including psychological and physical comfort, has become more and more important, and people have begun to pay attention to comfort perception that researchers rarely get involved in. Comfort is a subjective reflection of the human body. Only when the physiological, psychological, and physical factors interact in a satisfactory manner can a comfortable state be achieved. The physiological reaction of human body is the objective reaction of human body to external conditions in order to achieve a steady state, but the objective response may not truly reflect people's subjective feelings, or there are some differences between subjective and objective responses of the human body to external conditions. Human feelings cannot be measured and can only be judged by observing related reactions. The comfort sensory of the human body and the psychological feeling of dressing are the main evaluation indexes describing the psychological reaction of human body. Hu et al.¹ compared the objective measurements with subjective perceptions of moisture sensations during exercise, the results shows there existed a significant correlation between them. Grujic and Geršak² designed an experiment that subjects wore two different models of summer clothing (women's dresses and women's blouse plus shorts) made from different raw materials, they found that there is a relationship between subjective assessment of wearing comfort and physiological parameters (mean skin temperature, skin relative humidity, amount excreted in sweat absorbed in clothing). Suganthi and Senthilkumar³ conducted a wear trial for shuttle badminton players and they were ranked using thermal environment subjective judgment scale. Tadesse et al.⁴ used subjective evaluation technique for assessing the tactile comfort of some functional textile fabrics. Lee et al.⁵ evaluated the effect of the fabric for Bikram yoga clothing and fit measured in clothing pressure on the wearer's physiological response and perceptive sensation before and after exercise in hot conditions and during a resting period in standard conditions. They found that the feeling of comfort was different between before yoga and after resting. Teyeme et al.⁶ developed a questionnaire to evaluate the wear comfort of cycling outfits and address various key aspects such as tactile sensation, garment fit with reference to size, garment esthetics (style and shape), comfort (before, during, and after wearing) and overall satisfaction. The results show that the sensorial comfort was mainly correlated with fabric properties, fit and moisture sensation, and the thermophysiological comfort was affected by the fabric properties, the test environment conditions and level of activity. Wang et al.⁷ examined the effects of the clothing insulation distribution between half-bodies by Fanger's predicted mean vote model. The results indicated that different distribution index lead different

subjective thermal evaluations. Although many scholars have studied and analyzed the evaluation of human body comfort mainly by subjective evaluation method of comfort, most of them only used simple questionnaire to directly ask the subjects about their thermal comfort or pressure comfort after exercise, and then took the evaluation value after exercise or the average value of all motion state evaluations as the basis of the whole movement comfort evaluation.

Sportswear affects the proprioception and changes the movement action, thus optimizing the technical action is very important. Doan et al.⁸ proposed how custom-fit compression shorts affect athletic performance and to examine the mechanical properties of the shorts. Shimana et al.⁹ developed a new method for designing compression sportswear from the viewpoint of force which effect of these forces on physical exercise. Britto et al.¹⁰ analyzed the influence of a compressive garment on knee valgus during landing, they found the compressive garment decreased knee flexion and knee valgus range of motion. Zamporri and Aguinaldo¹¹ designed compression garments to prevent knee injuries by inducing changes in jumping mechanics. Silina et al.¹² Pointed out coverage of close-fit garments can affect the athlete's range of motion and hinder to reach the peak of athletic achievement, so they proposed sportswear should preserve athletes ergonomic and pressure comfort. Maleki et al.¹³ discussed the effect of fabric tensile property and garment size on the clothing pressure variation, and analyzed the pressure alteration during the body movement with various ranges. Wang¹⁴ studied the wearing comfort of elastic tights in riding state, measured the objective pressure and subjective comfort evaluation of key parts, combined with the skin stretch in riding state, and finally optimized its pattern. Therefore, the main concern of the comfort of sportswear should be motion comfort. Different sports intensity will produce different sports loads on the human body. In order to achieve the steady state of the body, the human body will have different physiological and psychological reactions, which are not limited to pressure or thermal-moisture or tactile comfort, but the comprehensive sensory comfort of the three or the two, namely pressure comfort, tactile comfort and thermal-moisture comfort. Therefore, for motion comfort, we should not only study one kind of comfort, because there will be different perceptions in the process of sports, in order to study motion comfort more comprehensively, this paper directly takes wearable comfort as the research object, and does not specify a certain kind of comfort. In addition, the comfort caused by different motion loads is quite different. The comfort evaluation values in different movements states should not be simply averaged as the basis for the comfort evaluation of the entire motion state. The comfort in every motion state should be evaluated and analyzed. Moreover, the human body is a complex system, and there are some differences in perception and reaction to different motion loads among

Textile	Fabric	Size/cm	width/cm
upper arm sleeve	elastic knitted fabric	upper arm circumference-1, upper arm circumference-2, upper arm circumference-3	5



Figure 1. Upper arm sleeve.

different parts. Therefore, specific research is needed, that is, to analyze the comfort of different parts. Only by understanding the comfort state of different parts in every motion state can we better design tight-fitting sportswear, ensure the wearable comfort during movement and improve sports performance. In a word, the overall comfort of the human body will be affected by the comfort of every part of the human body during the movement of the human body, so it is very necessary to study the local comfort and the overall comfort of the human body. The research on the comfort of tight-fitting sportswear mostly focuses on the research of overall comfort, and there are few researches on the local comfort, as well as the research on the relationship between local comfort and overall comfort. Most of the existing researches on subjective comfort take dynamic comfort as a whole, but the influencing factors are different in different motion states, so it is unreasonable to study movements comfort as a whole. In order to study the influencing factors of overall comfort in every movement state, this paper adopts Analytic Hierarchy Process-Entropy weight, Fuzzy-Rough Set Theory, Analytic Hierarchy Process-Structural Equation Model (AHP-SEM), Particle Swarm Optimization-Cuckoo Search (PSO-CS) to optimize the influencing index of overall comfort in every dynamic state, and then verify Adaptive Network-based Fuzzy Influence System (ANFIS) model to obtain the best model of index optimization. This research will provide a more accurate design basis for the comfort of tight-fitting sportswear and favorable technical guidance for maximizing motion comfort, proposes a new research method and theory for improving the quality of tight-fitting sportswear, which is perfect to a certain extent evaluation standard for comfort of tight-fitting sportswear.

Experiment

Selection and training of subjects

Eight healthy young men with similar age, size, and hobbies were selected. They all have long-term running experience, were all graduate students majoring in clothing and have sufficient knowledge of ergonomics. They were taken to the climate room for temperature, humidity, and pressure sensitivity tests. More details are as follows.

The room temperature of the climate chamber can be controlled between -5°C and 42°C with an accuracy $\pm 0.5^{\circ}\text{C}$. The relative humidity of the room can be controlled between 10% and 85% with an accuracy $\pm 5\%$.

Without being informed of the temperature and humidity of the environment, and under the control of the laboratory teacher in charge of the experiment, the temperature will increase or decrease by 2°C every 10 min under the condition that other climatic parameters such as humidity and windy speed which are unchanged, because every 1°C increase in air temperature, the average temperature of human skin will increase by 0.3246°C ,¹⁵ while the temperature of human skin will change by 2°C , and the thermal sensation of human body will change by at least one division.¹⁶ And ask every subject about their feelings and eliminate those who are insensitive to temperature. And then, under the condition that other climate chamber parameters such as temperature and windy speed which are unchanged, increase or decrease humidity of the climate chamber, ask everyone's feelings, eliminate subjects who are not sensitive to humidity. And finally carry out pressure sensitivity testing on the remaining subjects.

At first, we measured the upper arm circumference of the remaining subjects in turn, and sewed three simple upper arm sleeves (their dimensions are the average upper arm circumference subtract 1, subtract 2, and subtract 3, respectively) for every subject with knitted fabric with good elasticity (see Figure 1). The subjects put these sleeves on their upper arms in turn, and do some arm lifting and bending actions to test their sensitivity to pressure. After the test, the remaining five subjects in total were the participants of the whole experiment.

During the temperature, humidity, and pressure sensitivity tests, in order to avoid the influence of other people's answers to environmental changes (herd effect), to ensure that when a certain subject answers to environmental climate changes, the non-respondents can't hear it, everyone should wear earplugs, and then ask everyone in turn.

And five young men (named M1, M2, . . . M5) were selected as participants in this experiment. See Table 1 for their body shape parameters.

Table 1. Subjects' body parameters.

No.	Age	Bust (cm)	Waist (cm)	Height (cm)	Shoulder (cm)	Thigh girth (cm)	Arm girth (cm)	Upper hip girth (cm)	Lower hip girth (cm)	BMI
M1	26	100.5	83.8	176.8	42.9	61.5	33.1	91.5	100.8	23.0
M2	28	100.2	88.9	178.2	42.6	63.3	33.0	92.4	102.6	23.6
M3	28	99.8	86.6	176.5	42.7	61.2	33.3	93.1	101.4	22.5
M4	26	101.6	85.3	177.0	42.7	60.9	33.1	91.2	100.7	23.3
M5	27	99.5	84.2	176.7	42.7	61.7	33.0	91.9	101.6	22.4

BMI = Weight (kg) ÷ Height (m)².

Table 2. Fabric parameters of tights.

Tight garment	Size	Fabric component	Thickness (mm)	Grammage (g m ⁻²)	Longitudinal fabric density/coil number (5 cm) ⁻¹	Horizontal fabric density/coil number (5 cm) ⁻¹
T1	M	91%Polyester, 9%Spandex	0.94	153.3	136.5	88.5
T2	M	75%Polyester, 25%Polyamide fiber or nylon	0.60	181.1	99.0	103.5
T3	M	70%Polyester, 26%Nylon, 4%Spandex	0.66	230.8	178.0	93.5
P1	M	91%Polyester, 9%Spandex	0.99	305.7	180.5	116.0
P2	M	72%Polyester, 28%Spandex	1.14	334.2	143.5	96.0
P3	M	87%Polyester, 13%Spandex	0.98	237.5	129.5	110.0



Experimental clothing

According to the average body size of five subjects, three tight tops (T1, T2, T3) and three tight trousers (P1, P2, P3) were purchased from Decathlon store (All tops' styles are the same or similar and all trousers' styles are the same or similar, the specific information of tops and trousers are all shown in Table 2). Tops and trousers should be freely combined for trying-on, there are a total of nine sets of combined tights, which were labeled T1P1, T2P2, T3P3, T1P2, T2P3, T3P1, T1P3, T2P1, T3P2. During the whole experiment, five subjects wore nine sets of combined experimental tights in turn, so there were 45 questionnaires in total. And until every subject tried on all tight-fitting combinations (tops + trousers) in turn, wearing trials can be finished. The experiment take us nearly 8 days in total to finish testing.

Experimental environment and requirements

- (1) The simulation experiment was carried out in a climate room, with an average temperature of 5.1°C, a humidity of 78% and an average wind speed of 19.1 km/h (realized by a high-power electric fan).
- (2) Before participating in the experiment, the subjects must keep a good mood and emotion.
- (3) Before the experiment, ensure that all experimental tights are restored to their original state and placed in the climate room for 24 h.
- (4) Testers randomly select and try them on in turn without being told about the fabric of tights.
- (5) Before the experiment, all subjects were given a unified explanation of the questionnaire, so as to ensure that all subjects have the same understanding of the questionnaire content and scale, and

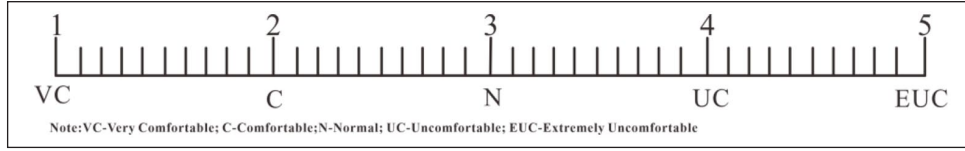


Figure 2. Comfort evaluation scale.

Table 3. Comfort evaluation of M3 trying on T2P1.

Posture	BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10	BM11	BM12	BM13	BM14	BM15	BM16	BM17	BM18	BM19	OM
Standing	2.0	2.1	2.9	2.1	1.6	1.6	1.5	1.2	2.0	2.2	2.1	2.7	2.4	2.3	2.4	2.2	2.1	2.5	2.4	2.4
Jumping	2.6	2.2	3.6	2.8	2.1	3.7	2.0	2.1	2.2	2.1	2.1	2.8	2.1	2.2	2.2	2.1	2.0	2.3	3.4	3.2
Squat	2.2	2.1	2.4	2.2	2.2	2.6	2.3	2.8	2.2	1.9	1.8	1.8	1.6	1.7	2.1	2.0	2.1	2.6	2.2	2.4
Squat down	2.3	2.0	2.3	2.3	2.4	2.8	2.2	3.0	2.5	1.8	1.8	1.9	1.7	1.7	2.5	2.2	2.1	2.8	2.4	2.8
Jogging	3.2	3.0	4.7	4.3	3.8	3.8	4.7	3.1	4.3	2.3	2.2	3.0	2.3	2.1	4.6	3.7	3.6	3.0	3.3	4.5
Walking	3.1	3.1	4.2	4.6	3.4	3.5	3.8	3.0	4.5	2.2	2.2	2.8	2.1	2.0	4.7	3.5	3.4	3.1	3.5	4.3
Lifting legs	2.4	2.3	3.4	3.0	2.9	3.3	2.5	3.7	3.3	2.5	2.3	2.6	2.2	2.2	4.1	3.3	3.2	3.0	3.0	3.6
Rest	2.1	2.1	3.0	2.8	2.5	3.6	2.2	3.0	3.4	2.2	2.2	2.1	2.1	2.2	3.5	3.0	3.1	2.5	2.5	3.3

eliminate the systematic error of the experiment as much as possible.

Experimental content

The whole test process is divided into eight test stages, specifically as follows: preparing (20 min, adapt to the testing environment) → standing (10 min) → jumping (10 min) → squat (10 min) → squat down (10 min, 1 min as a group, rest 0.5 min after a group) → jogging (10 min, average speed: 5.5 km/h) → walking (10 min, average speed: 4.3 km/h) → lifting legs (10 min, left and right legs are raised alternately, 1 min as a group, rest 0.5 min after a group) → rest (10 min) → experiment end. Among them, during the standing process, the subjects all have limb movements, such as bending over, lifting their arms horizontally, lifting their arms vertically and lifting their arms laterally by 45°. At the end of every test phase, the staff shall record the subjective comfort evaluation value of every part and the whole.

By summing up the existing research and the authors' research experience, this paper regards the shoulder, armpit, bust, back, back waist, body side, upper arm (inside and outside upper arm), elbow, forearm (inside and outside forearm), hip, thigh (inside thigh, outside thigh, back thigh), knee, shank, abdomen, and crotch as the initial evaluation parts of local comfort.^{17–23}

Evaluation scale

Comfort types of every part and overall comfort is evaluated subjectively according to ISO 10551-2001 "Ergonomics of Thermal Environment Assessing the Influence of Thermal Environment by Subjective Judgment

Scale," which means very comfortable, comfortable, normal, uncomfortable, and extremely uncomfortable, as shown in Figure 2.

Comfort data collection

The comfort of shoulder, armpit, bust, back, back waist, abdomen, body side, hip, crotch, inside upper arm, outside upper arm, elbow, inside forearm, outside forearm, inside thigh, outside thigh, back thigh, knee, shank are recorded as BM1, BM2, . . . , BM19, overall comfort is recorded as OM. Because there are 45 questionnaires in total, this paper only takes the comfort evaluation of M3 trying on T2P1 as an example, as shown in Table 3.

The comfort evaluation data of 45 questionnaires form the original data matrix according to the experimental stage, which are as follows: $(S_{\text{standing}})_{45 \times 20}$, $(S_{\text{jumping}})_{45 \times 20}$, $(S_{\text{squat}})_{45 \times 20}$, $(S_{\text{squat down}})_{45 \times 20}$, $(S_{\text{jogging}})_{45 \times 20}$, $(S_{\text{walking}})_{45 \times 20}$, $(S_{\text{lifting legs}})_{45 \times 20}$, $(S_{\text{rest}})_{45 \times 20}$. For example, the data matrix of comfort and overall comfort evaluation of every part in the standing state $(S_{\text{standing}})_{45 \times 20}$:

$$(S_{\text{standing}})_{45 \times 20} = \begin{bmatrix} S_{M1-T1P1}^{BM1} & S_{M1-T1P1}^{BM2} & \dots & S_{M1-T1P1}^{OM} \\ S_{M2-T2P2}^{BM1} & S_{M2-T2P2}^{BM2} & \dots & S_{M2-T2P2}^{OM} \\ \vdots & \vdots & \vdots & \vdots \\ S_{M3-T3P3}^{BM1} & S_{M3-T3P3}^{BM2} & \dots & S_{M3-T3P3}^{OM} \end{bmatrix} \quad (1)$$

Where, $(S_{\text{standing}})_{45 \times 20}$ indicates the evaluation data matrix of every part and overall comfort when all subjects wear nine sets of combined experimental tight in turn when indicating the standing state; $S_{M1-T1P1}^{BM1}$ indicates the comfort evaluation value of the BM1 (i.e. shoulder) when the subject M1 wore T1P1; $S_{M1-T1P1}^{BM2}$ indicates the comfort evaluation value

of the BM2 (i.e. armpit) when subject M1 wore T1P1; $S^{OM}_{M1-T1P1}$ indicates the comfort evaluation value of the OM (i.e. overall comfort) when subject M1 wore T1P1; $S^{BM1}_{M3-T3P3}$ indicates the comfort evaluation value of the BM1 (i.e. shoulder) when subject M3 wore T3P3.

Modeling

When evaluating tights, most people choose as many comfort-related indicators as possible. However, this approach can easily lead to the complexity of the evaluation process, and even affect the evaluation results of comfort. Because some indicators have little contribution to the evaluation of comfort, in order to make the evaluation results comprehensive and accurate, it is necessary to reduce the indicators that have little impact on the evaluation results before the comfort evaluation, that is, dimensionality reduction. In this paper, AHP-Entropy weight, Fuzzy-Rough Set Theory, AHP-SEM, PSO-CS were used to optimize the part indexes, and then their optimized indexes are used as input parameters, and then the ANFIS model was used to predict the comfort of every experimental stage. In finally, by comparing comfort prediction values with the real values of the comfort, the better index optimization model and the best prediction indexes are found out.

Index preprocessing

Before using AHP-Entropy weight, Fuzzy-Rough Set Theory, AHP-SEM, PSO-CS to optimize the position index, the index dimension should be reduced, in order to eliminate redundant indexes and improve the accuracy of prediction results. Because the establishment of a good index system is the key to evaluate the comfort of tight-fitting sportswear, the index system in this paper is based on the subjective evaluation when subjects wear it. Although these evaluations can effectively use the actual meaning of the indicators, they cause the problems of redundant information content and weak discrimination ability when screening the indicators. Therefore, the complicated index layer (i.e. secondary indexes, index of every part of the human body) is simplified, and a small number of effective indexes are used to predict the overall comfort behavior, at the same time, the difficulty of subjective evaluation will be reduced.

Index dimension reduction. Sum of Squares of Deviations is used for R clustering of evaluation indexes. At first, the Sum of Squares of Deviations of every index is calculated, and the final cluster number is determined with the goal of minimizing the Sum of Squares for Total of all clusters.

Sum of Squares of Deviations of every index:

$$D_i = \sum_{j=1}^{n_i} (A_i^j - \bar{A}_i) (A_i^j - \bar{A}_i) \quad (2)$$

Sum of Squares for Total of all clusters:

$$D_i = \sum_{i=1}^K \sum_{j=1}^{n_i} (A_i^j - \bar{A}_i) (A_i^j - \bar{A}_i) \quad (3)$$

Where, D_i represents the Sum of Squares of Deviations of evaluation indexes of the i th clustering, $n=1, 2, \dots, m$; N_i represents the number of evaluation indexes of the i th clustering; A_i^j represents the normalized sample value vector of the j th evaluation index in the i th clustering, $j=1, 2, \dots, m$; \bar{A}_i represents the vector of the average value of the i th clustering index samples.

Test of dimension reduction effect of index. The number of R clustering is set subjectively. Non-parametric K-W test is carried out for every kind of indexes after clustering, to test whether there are significant differences in numerical values of similar indexes, so as to judge whether the number of clusters is reasonable. If the significance level value Sig. of every kind of index is greater than 0.05, it indicates that there is no significant difference in similar indexes after clustering, that is, the number of clusters is reasonable.

Preliminary screening of indicators. The index information content in every clustering is analyzed by coefficient of variation. The larger the coefficient of variation of the index is, the stronger the information separation ability of the index is, and the better it can represent other indicators in the same category to represent the overall comfort. Coefficient of variation formula is as follows:

$$V_j = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (V_{ij} - \bar{V}_j)^2}}{\bar{V}_j} \quad (4)$$

Where, V_j represents the coefficient of variation of the j th index in every experimental stage; n represents the number of objects to be evaluated; \bar{V}_j indicates the j th index of every test stage, and the average value of comfort evaluation of this part when all subjects wear nine sets of combined experimental tights in turn; V_{ij} indicates the comfort evaluation of the i th index and the j th try-on in every test stage.

Taking the preliminary screening results of indicators in the standing state as an example, the clustering process is illustrated. Substitute the indexes data into formula (2) and formula (3), and cluster the indexes data into four categories by SPSS 23.0. The clustering results are shown in Table 4.

It can be seen from Table 4, the K-W test Sig. Values are all more than 0.05. R-clustering and coefficient of variation index screening model were used to screen 19 standardized indexes data, and nine evaluation indexes were retained as the initial indexes of the overall comfort model (i.e. AHP-Entropy weight, Fuzzy Rough Set Theory, AHP-SEM, PSO-CS) when standing, which were bust, abdomen,

Table 4. Preliminary screening of indicators in standing state.

Indexes	Category	K-W testing Sig.	Coefficient of variation	Y/N
BM1	2	0.579	0.108	N
BM2	1	0.635	0.551	N
BM3	1	0.635	0.703	Y
BM4	2	0.579	0.357	N
BM5	2	0.579	0.234	N
BM6	1	0.635	0.680	Y
BM7	2	0.579	0.431	N
BM8	4	0.714	0.333	N
BM9	4	0.714	0.695	Y
BM10	1	0.635	0.419	N
BM11	1	0.635	0.443	N
BM12	1	0.635	0.722	Y
BM13	2	0.579	0.698	Y
BM14	2	0.579	0.382	N
BM15	3	0.582	0.803	Y
BM16	3	0.582	0.527	N
BM17	3	0.582	0.779	Y
BM18	3	0.582	0.768	Y
BM19	3	0.582	0.651	Y

Y-Will be as evaluation indexes of the overall comfort; N-Will not be as evaluation indexes of the overall comfort.

elbow, inside forearm, inside thigh, back thigh, knee, shank, and crotch. Most of these indicators are concentrated in limbs. Through the coefficient of variation, it is preliminarily known that the upper body comfort is mainly affected by bust (0.703) and abdomen (0.680), inside thigh (0.803), back thigh (0.779), knee (0.768) and elbow (0.722), and the lower body comfort is mainly affected by the crotch.

The preliminary screening results of indexes under various sports conditions were obtained, as shown in Table 5.

It can be seen from Table 5 that there are many differences in the influencing indicators of overall comfort under different sports conditions. When the human body is in the state of squat, squat down, and lifting legs, the main influencing factors of overall comfort are the lower limbs, which may be due to the large activity of the lower body. In the state of jogging, walking, and rest, the main factors affecting the overall comfort are concentrated in the upper body. These indexes are only preliminary optimization, and can't be used as the parts to characterize the overall comfort of every movement state (i.e. every experimental stage). These preliminary screening indicators should be selected as the final indicators through AHP-Entropy weight, Fuzzy Rough Set Theory, AHP-SEM, and PSO-CS.

AHP-Entropy weight evaluation model

Analytic Hierarchy Process (AHP), as a mathematical method combining qualitative and quantitative analysis, could get the importance sequence of all indexes, that is, the

Table 5. Preliminary screening results affecting the overall comfort of every test stage.

Posture	Preliminary screening results
Standing	BM3, BM6, BM12, BM13, BM15, BM17, BM18, BM19
Jumping	BM1, BM3, BM6, BM8, BM10, BM12, BM15, BM18, BM19
Squat	BM5, BM6, BM7, BM8, BM15, BM18, BM19
Squat down	BM5, BM6, BM7, BM8, BM15, BM17, BM18, BM19
Jogging	BM2, BM3, BM4, BM6, BM7, BM8, BM9, BM10, BM15, BM18, BM19
Walking	BM2, BM3, BM4, BM7, BM9, BM10, BM15, BM18, BM19
Lifting legs	BM8, BM15, BM17, BM18
Rest	BM2, BM3, BM4, BM6, BM9, BM19

weight sequence, by calculating the pairwise importance evaluation matrix of indicators at all levels. However, when using qualitative method to construct the evaluation matrix, this method is easily interfered by subjective factors, which will lead to the loss of decision information of the discrimination matrix and makes the discrimination result too subjective.^{24,25} Entropy weight method could use information entropy to reflect the effective amount of information to obtain the weight of indexes, which belongs to objective discrimination method. Although using entropy weight method to discriminate and analyze indexes has a solid mathematical theoretical support, entropy weight method does not consider the influence of subjective factors on the analysis process, and relies too much on objective data, so its evaluation results are vulnerable to data fluctuations, which easily leads to the evaluation results being too objective. Therefore, the combination of AHP and Entropy weight method can effectively utilize the experience and professional knowledge of the subjects, and at the same time effectively utilize the objective information of the data, thus avoiding judgments that are too subjective or too objective. Finally, the comprehensive weight of every index is obtained by AHP and Entropy weight method, and the index which has less influence on comfort evaluation is removed, so as to reduce the dimension of the index.

AHP-Entropy weight evaluation method has better advantages in evaluating fuzzy nonlinear problems. The basic idea of using AHP-Entropy weight method is as follows:

- (1) Determine the evaluation index level of the evaluation object. The evaluation subject U is divided into m evaluation dimensions, that is, $U = \{U_1, U_2, \dots, U_m\}$, and secondary evaluation indicators $S\sigma = \{S\sigma_1, S\sigma_2, \dots, S\sigma_n\}$ are obtained under different dimensions, where n represents the number of secondary indicators under a specific evaluation dimension.

Table 6. Body parts indexes.

The first-class indexes	Secondary indexes	Description
Upper body	Shoulder	Evaluate the comfort of every part in the human body.
	Armpit	
	Bust	
	Back	
	Lumbar	
	Abdomen	
Lower body	Body side	
	Hip	
	Crotch	
Limbs	Inside upper arm	
	Outside upper arm	
	Elbow	
	Inside forearm	
	Outside forearm	
	Inside thigh	
	Outside thigh	
	Back thigh	
	Knee	
	Shank	

(2) Construct judgment matrix J.

The first-class indexes of every experimental stage (i.e. every motion state) are upper body, lower body, and limbs. Secondary-class indexes are shoulder, armpit, etc., as shown in Table 6. During the experiment, at the end of every experimental stage, the subjects were asked about the comfort of different parts and overall body, according to the subject's feelings during wearing, the subjects compare the importance of every layer of comfort index in every experiment state, score according to Table 7 and get the judgment matrix J:

The judgment matrix is obtained by pairwise comparison of n indexes: $J=(a_{ij})_{n \times n}$, where, $a_{ij} > 0$, $a_{ij} = 1/a_{ji}$, $i=1, 2, \dots, n$; $j=1, 2, \dots, n$.

(3) According to the definition of Entropy, the Entropy value and Entropy weight of evaluation index are determined.

$$\begin{aligned}
 H_j &= -k \sum_{i=1}^m f_{ij} \ln f_{ij} \\
 f_{ij} &= x_{ij} / \sum_{i=1}^m x_{ij} \\
 x_{ij} &= \frac{a_{ij} - \min\{a_i\}}{\max\{a_i\} - \min\{a_i\}} \\
 d_j &= \frac{1 - H_j}{m - \sum_{i=1}^m H_j}
 \end{aligned} \quad (5)$$

Where, H_j represents the Entropy of the j th index; f_{ij} represents the proportion of the subjective weight of the j th subject to the i th index, if $f_{ij} = 0$, so $f_{ij} \ln f_{ij} = 0$. x_{ij} indicates the standard value of every sub-index data in index i ; a_{ij} indicates the data value of sub-index j in index i ; $\max\{a_i\}$, $\min\{a_i\}$ respectively represent the maximum value and minimum value of every sub-item data value in index i ; d_j represents the Entropy weight of the j th index.

(4) Determine the comprehensive weight. According to the subjective weight obtained by AHP and the objective weight obtained by entropy weight, the linear weighting method is adopted to obtain the comprehensive weight, which comprehensively considers the subjectivity and objectivity and has good convincing power.

$$W_i = \mu w_i' + (1 - \mu) w_i'' \quad (6)$$

Where, W_i represents the comprehensive weight; μ represents subjective and objective weight distribution value, $\mu=0.5$; w_i' represents the weight obtained by AHP, that is, subjective weight; w_i'' indicates the weight obtained by entropy weight method, that is, objective weight.

Fuzzy Rough Set theory model

Combining Fuzzy Rough Set with comprehensive evaluation, the Fuzzy Rough Set theory is used to obtain the indexes that have great influence on the evaluation results, thus simplifying the evaluation process without affecting the evaluation results.²⁶⁻²⁹ In the Fuzzy Rough Set theory, the decision table is composed of conditional attributes and decision attributes. The decision table in this paper is composed of comfort evaluation of every part (i.e. the subjects' scores of every part according to their wearing feelings), in which conditional attributes refer to the parts of the human body that affect the overall comfort, while decision attributes refer to the comfort scores of every part of the human body.

Specific steps:

(1) Construct membership function

The approximate space $S=(U, R)$, where R is a fuzzy equivalent relation on the universe U . if $X \in U$, then X is a membership function of the upper R_X' and lower approximate sets R_X'' of R .

$$\begin{aligned}
 \delta_{R_X'}(F_i) &= \inf_{x \in U} \max\{\delta_{F_i}(x), \delta_X(x)\} \\
 \delta_{R_X''}(F_i) &= \inf_{x \in U} \max\{1 - \delta_{F_i}(x), \delta_X(x)\}
 \end{aligned} \quad (7)$$

(2) Membership function of fuzzy positive domain

Table 7. Setting the standard group of values (i.e. the scaling method of judgment matrix a_{ij}).

No.	Comparison values	Meaning
1	1	Two factors i have the same importance as j
2	3	Two factors i are slightly more important than j .
3	5	Two factors i compared with j , the former is obviously more important than the latter
4	7	Two factors i compared with j , the former is more important than the latter
5	9	Two factors i compared with j , the former is extremely important than the latter
6	2, 4, 6, 8	Median value of the above two adjacent judgments
Reciprocal	If the ratio of importance of factor i to factor j is a_{ij} , then the ratio of importance of factor j to i is $a_{ji} = 1/a_{ij}$	

For $\forall x \in U$, the membership degree of x to fuzzy positive domain is: $\delta_{pos_r(Q)}(x) = \sup_{x \in U/Q} \max \{ \delta_{R_x}(x) \}$

(3) Attribute dependency function

The dependence of decision attribute Q on conditional attribute P is

$$\gamma_P(Q) = \frac{\sum_{x \in U/Q} \delta_{pos_r(Q)}(x)}{|U|} \quad (8)$$

AHP-SEM model

Combining Structural Equation Modeling (SEM) with Analytic Hierarchy Process (AHP), the comprehensive weight is determined and the comfort evaluation index system is constructed. AHP is a commonly used method of weight calculation subjectively. However, it is too subjective to objectively reflect the actual situation because it only compares two indexes of a complex problem by AHP and the weights are determined by expert scores. SEM method is a confirmatory analysis method, which can not only deal with the relationship among multiple variables and attach importance to the application of multiple statistical indicators, but also reflect the weight information of indicators in the correlation.³⁰⁻³³ However, SEM METHOD overcomes the influence of experts' subjective factors to a certain extent, but it is easily influenced by the selection of sample data. When the sample data is not comprehensive, the obtained weights may seriously deviate from reality. Therefore, this paper adopts the method of combining SEM and AHP to calculate the weight. SEM can obtain objective index weight information, and AHP can make full use of the experience and knowledge of experts in related fields to obtain subjective evaluation results of the importance of indicators.

$$W_i = \lambda A_i + (1 - \lambda) O_i \quad (9)$$

Where, A_i indicates subjective weight; O_i represents objective weight, and the value range of λ is $[0,1]$, and the specific value depends on the actual situation.

PSO-CS model

Particle Swarm Optimization (PSO) and Cuckoo Search (CS) are both swarm bionic intelligent algorithms, which have different performances in global search ability and convergence speed. PSO algorithm has strong local search ability and easy convergence, but it is easy to fall into local optimum. CS algorithm has sufficient global searching ability, but it has weak local searching ability and is not easy to converge. Combining the advantages of Particle Swarm Optimization (PSO) and Cuckoo Search algorithm, a new method for optimizing comfort prediction index is proposed.

According to the principle that every particle in particle swarm optimization is moving toward the current global optimum and every particle searches for the current local optimum, after every Levi flight, an improved particle algorithm is used to update the result solution position of Levi flight, so that every bird nest in cuckoo algorithm can move toward the global optimum and local optimum just like every particle in particle swarm optimization.³⁴⁻³⁶ The combination of PSO and CS not only keeps the randomness of searching, but also reduces the blindness of searching and accelerates the convergence of particles to the optimal solution. At the same time, the random elimination mechanism of CS algorithm makes the algorithm escape from local optimum smoothly, thus improving the performance of CS algorithm. Basic flow of PSO-CS algorithm:

- (1) Parameter of PSO-CS algorithm are initialized, that numb of nests n , the maximum iteration times N_{max} , the discovery probability P_a , the inertia weights w_{max} , w_{min} , the learn factors c_1 , c_2 , and the upper limits U_b and lower limits L_b of the search domain. Random initialization of bird's nest position $P_0^{t=0}$, the initial velocity $v_0^{t=0}$ and the initial optimal individual $P_{best} = P_0$, and the optimal target value in P_0 was defined as the initial population optimal G_{best} .
- (2) Inertialweight: $\omega = \omega_{max} - (\omega_{max} - \omega_{min}) * t / N_{max}$. Update matrix of bird's nest i position and particle velocity: $v_i^{t+1} = \omega v_i^t + c_1 \alpha_1 (G_{best} - P_i^t) + c_2 \alpha_2 (P_{best} - P_i^t)$, $P_i^{t+1} = P_i^t + v_i^{t+1}$. Where, α_1 , α_2 are random numbers from 0 to 1, P_i^{t+1} is a new nest location matrix

Table 8. Comparison of optimization results of indicators.

Posture	AHP-Entropy weight	Fuzzy-Rough Set Theory	AHP-SEM	PSO-CS
Standing	BM3 (0.102), BM6 (0.021), BM12 (0.154)*, BM13 (0.126), BM15 (0.156)*, BM17 (0.063), BM18 (0.209)*, BM19 (0.168)*	BM3 (0.250)*, BM6 (0.040), BM12 (0.097), BM13 (0.107), BM15 (0.246)*, BM17 (0.043), BM18 (0.165)*, BM19 (0.054)	BM3 (0.050), BM6 (0.375)*, BM12 (0.231)*, BM13 (0.016), BM15 (0.038), BM17 (0.072), BM18 (0.048), BM19 (0.169)*	BM3*, BM12*, BM15*, BM18*
Jumping	BM1(0.021), BM3(0.243)*, BM6 (0.179)*, BM8 (0.156)*, BM10 (0.040), BM12 (0.027), BM15 (0.045), BM18 (0.011), BM19 (0.277)*	BM1 (0.060), BM3 (0.082), BM6 (0.231)*, BM8 (0.038), BM10 (0.098), BM12 (0.172)*, BM15 (0.106), BM18 (0.019), BM19 (0.193)*	BM1 (0.036), BM3 (0.164)*, BM6 (107), BM8 (0.082), BM10 (0.110), BM12 (0.050), BM15 (0.203)*, BM18 (0.154)*, BM19 (0.093)	BM3*, BM6*, BM19*
Squat	BM5 (0.017), BM6 (0.382)*, BM7 (0.046), BM8 (0.261)*, BM15 (0.072), BM18 (0.065), BM19 (0.157)*	BM5 (0.072), BM6 (0.170)*, BM7 (0.248)*, BM8 (0.101), BM15 (0.106), BM18 (0.183)*, BM19 (0.119)	BM5 (0.226)*, BM6 (0.082), BM7 (0.165)*, BM8 (0.373)*, BM15 (0.066), BM18 (0.085), BM19 (0.002)	BM6*, BM8*, BM18*
Squat down	BM5 (0.034), BM6 (0.270)*, BM7 (0.017), BM8 (0.332)*, BM15 (0.023), BM17 (0.029), BM18 (0.281)*, BM19 (0.014)	BM5 (0.126), BM6 (0.013), BM7 (0.100), BM8 (0.202)*, BM15 (0.069), BM17 (0.237)*, BM18 (0.101), BM19 (0.151)*	BM5 (0.081), BM6 (0.188)*, BM7 (0.034), BM8 (0.185)*, BM15 (0.112), BM17 (0.109), BM18 (0.170)*, BM19 (0.131)	BM6*, BM8*, BM15*, BM18*
Jogging	BM2 (0.059), BM3 (0.172)*, BM4 (0.243)*, BM6 (0.020), BM7 (0.042), BM8 (0.026), BM9 (0.139), BM10 (0.055), BM15 (0.213)*, BM18 (0.029), BM19 (0.012)	BM2 (0.124), BM3 (0.118), BM4 (0.075), BM6 (0.120), BM7 (0.045), BM8 (0.102), BM9 (0.008), BM10 (0.153)*, BM15 (0.164)*, BM18 (0.028), BM19 (0.063)	BM2 (0.070), BM3 (0.023), BM4 (0.018), BM6 (0.035), BM7 (0.053), BM8 (0.244)*, BM9 (0.038), BM10 (0.138), BM15 (0.238)*, BM18 (0.106), BM19 (0.036)	BM3*, BM4*, BM7*, BM9*, BM15*
Walking	BM2 (0.171)*, BM3 (0.084), BM4 (0.199)*, BM7 (0.011), BM9 (0.179)*, BM10 (0.019), BM15 (0.201)*, BM18 (0.015), BM19 (0.121)	BM2 (0.027), BM3 (0.011), BM4 (0.123), BM7 (0.196)*, BM9 (0.167)*, BM10 (0.096), BM15 (0.100), BM18 (0.191)*, BM19 (0.088)	BM2 (0.196)*, BM3 (0.104), BM4 (0.180)*, BM7 (0.113), BM9 (0.069), BM10 (0.029), BM15 (0.092), BM18 (0.159)*, BM19 (0.057)	BM4*, BM9*, BM15*, BM19*
Lifting legs	BM8 (0.208)*, BM15 (0.419)*, BM17 (0.139), BM18 (0.233)*	BM8 (0.147), BM15 (0.295)*, BM17 (0.447)*, BM18 (0.111)	BM8 (0.389)*, BM15 (0.037), BM17 (0.285)*, BM18 (0.290)*	BM8*, BM15*
Rest	BM2 (0.344)*, BM3 (0.123), BM4 (0.310)*, BM6 (0.156)*, BM9 (0.045), BM19 (0.022)	BM2 (0.026), BM3 (0.251)*, BM4 (0.054), BM6 (0.210)*, BM9 (0.221)*, BM19 (0.238)*	BM2 (0.212)*, BM3 (0.103), BM4 (0.216)*, BM6 (0.183)*, BM9 (0.122), BM19 (0.164)*	BM4*, BM6*, BM9*

“*” are the final indexes to characterize the overall comfort.

- (3) The target values of P_0^t and P_1^t are calculated, and the nest positions in the top n of the target values corresponding to the number n of nests are selected to form P_2^t . Every nest in P_2^t is eliminated with a random probability of uniform distribution, and the random elimination probability matrix $C=(C_1, C_2, \dots, C_n)$ of every nest is compared with the discovery probability Pa .

$$P_{3,i}^t = \begin{cases} P_{3,i}^t, & \text{if } C_i \leq Pa \\ L_b + (U_b - L_b) * randn(n,1), & \text{else} \end{cases} \quad (10)$$

Where, U_b, L_b are the upper and lower bounds of optimization; $randn(n,1)$ is a normal distribution with mean value n and variance value 1.

- (4) Calculate the target values of P_2^t and P_3^t , select the bird’s nest positions in the top n of the target values corresponding to the number of bird’s nests n to

form P_4^t , extract the bird’s nest position with the best quality in P_4^t , and record it as Z_{best^t} , judge whether it meets the iteration times or error requirements, if so, stop and output the optimal solution; Otherwise, compare P_4^t with P_0^t , update individual best P_{best} and group best G_{best} , make $P_4^t = P_0^t$, $t = t + 1$, go to step (2) and enter the next iteration.

Results and discussion

Optimization results of different models

The overall comfort impact indicators of every test stage (i.e. different exercise states) are screened according to the weight, as shown in Table 8.

It can be seen from Table 8 that: (1) There are some differences in the indicators that affect the overall comfort in different sports states, that is, the comfort in different parts is quite different, mostly due to the different senses of thermal and moisture, pressure or tactile in different parts.

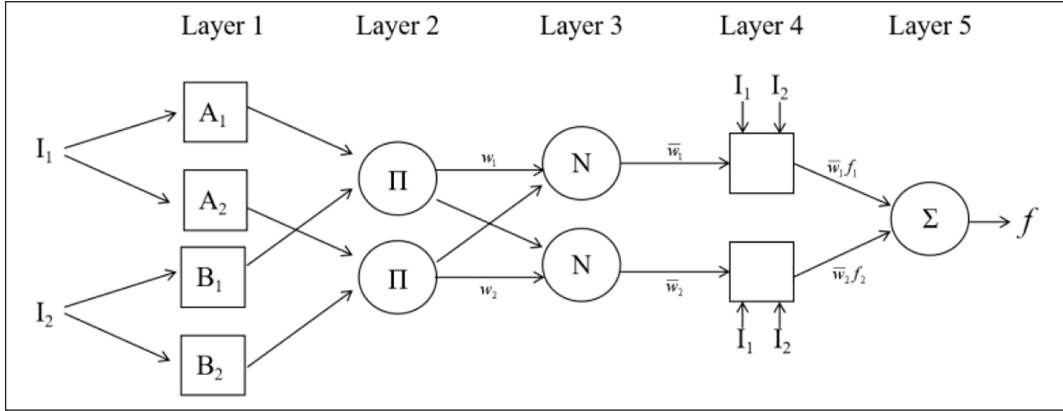


Figure 3. ANFIS model structure.

- (2) There are some differences in the optimization indexes of AHP-entropy weight, fuzzy rough set theory, AHP-SEM, and PSO-CS, among which, the optimization indexes of AHP- entropy weight and PSO-CS are similar, which shows that AHP-entropy weight, as an evaluation model combining subjectivity and objectivity, and intelligent model (PSO-CS) are similar to the overall comfort index optimization.
- (3) Observing the four models at every experiment state, the optimization level of the indexes when standing is similar, and most of the indexes optimized by the four models belong to limbs, which shows that the comfort of limbs has the greatest influence on the overall comfort when standing. Under other conditions, there are great differences in the impact indicators.

Simulation results verification and analysis

To verify the effectiveness of AHP-Entropy weight, Fuzzy Rough Set theory, AHP-SEM and PSO-CS in optimizing indexes, the indexes of every experimental state optimized by them are taken as input parameters and the corresponding overall comfort is taken as output parameters, and the prediction is made by the Adaptive Network-based Fuzzy Influence System (ANFIS) model. And then compare the prediction values with the real overall comfort evaluation values.

Model for verifying simulation results. In this paper, Adaptive Network-based Fuzzy Influence System (ANFIS) was used to test the validity of optimization indexes of every model. Adaptive Network-based Fuzzy Influence System (ANFIS), in fact, is also an artificial neural network model. ANFIS combines the advantages of neural network and fuzzy system, and makes up for the shortcomings of them. It can extract fuzzy rules from data sets well, adjust corresponding parameters by learning, simulate ideal input-output correspondence, and complete fuzzy classification

work well.³⁷⁻⁴⁰ The biggest feature of ANFIS model is modeling based on data, in which fuzzy membership function and fuzzy rules are obtained by learning input data. In a word, ANFIS network is an optimized model and a combined model. Fuzzy control theory can enhance the reasoning ability of neural network and increase the accuracy of the model, which can effectively improve the problem that the traditional artificial neural network is easy to fall into local minimum. The ANFIS model structure is shown in Figure 3.

Layer 1: Fuzzy segmentation layer. The nodes in this layer are all adaptive nodes, and their node functions are shown in Formula (11).

$$O_{1,i} = \begin{cases} \theta_{A_i}(I_1), i = 1, 2 \\ \theta_{B_i}(I_2), i = 1, 2 \end{cases} \quad (11)$$

Where, I_1, I_2 are the input of node i ; A_i, B_i are the “identification language” related to the node function value, such as “comfortable” or “uncomfortable”; $O_{1,i}$ is a membership function, which represents the degree to which I_1 and I_2 satisfy A_i and B_i , and usually adopts Gaussian function or bell function.

Layer 2: Rule reasoning layer. In Figure 3, Π is used to represent the nodes of this layer, that is, the input signals are multiplied and the output is

$$O_{2,i} = w_i = \theta_{A_i}(I_1) \cdot \theta_{B_i}(I_2), i = 1, 2 \quad (12)$$

Where, w_i represents that output signal, which is the expression of the excitation intensity of I_1 and I_2 under a certain rule.

Layer 3: Fuzzy layer. In the figure, the node of this layer is represented by N , and the i th node calculates the ratio of w_i of the i th rule to the sum of w values of all rules.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \quad (13)$$

Layer 4: Deblurring layer. For the adaptive node for parameter learning, the output node function is expressed as

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i I_1 + q_i I_2 + r_i) \tag{14}$$

Where, p_i, q_i, r_i are parameters learned in fuzzy rules.

Layer 4: Output layer. Marked by symbol Σ , the nodes are fixed, and the total output of the system is obtained

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{15}$$

Establishing steps of ANFIS model:

- ① Select sample data.
- ② The sample data are divided into two parts: training data and testing data. In this paper, the comfort questionnaires of M3 trying on T2P1, M2 trying on T1P1, M2 trying on T3P2 are randomly selected as the testing data, and others as the training data.
- ③ Set model training parameters.
- ④ Training model with training set data.
- ⑤ Verify model.

Analysis of prediction results. The prediction results of the overall comfort based on AHP-Entropy weight, Fuzzy Rough Set theory, AHP-SEM, and PSO-CS are shown in Table 9, and the error of the prediction results is shown in Figure 4. The smaller the error between the real value and the predicted value of the overall comfort is, the better the prediction index of the overall comfort is, that is, the model of the optimization index is better.

It can be seen from Table 9 and Figure 4 that the minimum average absolute error of the overall comfort of the four mixed models is 0.1485, that is, the maximum accuracy of the predicted value and the true value is about 85%. The maximum average absolute error is 0.3473, that is, the minimum accuracy between the predicted value and the true value is about 65%, the prediction level is higher.

The prediction performances of AHP-Entropy weight-ANFIS, Fuzzy-Rough Set Theory-ANFIS, AHP-SEM-ANFIS, and PSO-CS-ANFIS are quite different in every test stage, which shows that AHP-Entropy weight, fuzzy rough set theory, AHP-SEM, and PSO-CS have advantages and disadvantages in optimizing indexes. For example, as far as the predicted results and errors of overall comfort in the standing state are concerned, according to the average absolute errors, that is, the average absolute errors between the real and predicted values of overall comfort of M3 trying on T1P1, M2 trying on T1P1, and M2 trying on T3P2. It can be known that PSO-CS-ANFIS (mean absolute error:

Table 9. Comparison of predicted results of overall comfort.

Posture	Real value			AHP-Entropy weight-ANFIS			Fuzzy-Rough Set Theory-ANFIS			AHP-SEM-ANFIS			PSO-CS-ANFIS		
	Te1	Te2	Te3	Te1	Te2	Te3	Te1	Te2	Te3	Te1	Te2	Te3	Te1	Te2	Te3
Standing	3.1	2.8	2.4	3.3543	2.4223	2.3497	3.3381	3.6352	2.8635	3.4639	2.6925	3.304	2.7635	2.6204	2.5388
Jumping	3.3	3.0	3.2	3.4377	3.1945	3.1207	3.5089	2.7347	3.6324	3.4687	3.6643	2.3216	3.2985	2.8887	3.36525
Squat	3.3	2.8	2.4	3.5205	2.6843	2.6321	3.4916	2.6893	2.7083	3.5235	2.9672	2.46987	3.3686	2.7437	2.0363
Squat down	3.2	2.9	2.8	3.0752	2.9283	3.1050	3.5253	3.3767	2.83672	3.5799	3.23643	2.96348	3.4834	3.0911	2.7428
Jogging	4.3	3.5	4.5	4.5010	3.3875	4.4483	4.0631	3.5890	4.1351	4.2038	3.48721	4.3256	4.1918	3.5432	4.7683
Walking	4.0	3.2	4.3	4.2461	3.2853	4.5168	4.2047	3.2653	4.68723	4.2357	3.5673	4.5876	4.3659	3.0194	4.0064
Lifting legs	3.5	3.0	3.6	3.3589	3.402	3.7333	3.1073	3.3108	4.1126	3.8762	3.3336	3.3349	3.8796	2.8973	3.5910
Rest	3.3	2.9	3.3	3.4307	3.1876	3.43606	3.5793	3.2657	3.0276	3.5762	3.2363	3.2678	3.3058	3.2231	3.18767
Maximum absolute error				0.2543	0.4020	0.305	0.3927	0.8352	0.5126	0.3799	0.6643	0.9040	0.3796	0.3231	0.3637
Mean absolute error				0.1820	0.2005	0.1506	0.2597	0.3148	0.3473	0.2650	0.2907	0.3469	0.1937	0.1485	0.1760

Te1-M3 wore T2P1; Te2-M2wore T1P1; Te3-M2 wore T3P2.

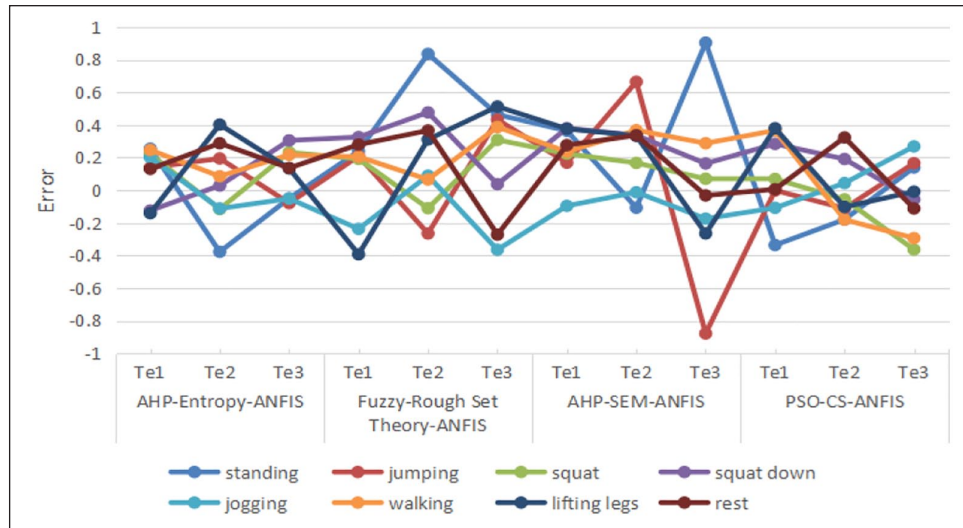


Figure 4. Comparison of error values of overall comfort prediction results.

0.2183) < AHP-Entropy weight-ANFIS (mean absolute error: 0.2274) < AHP-SEM-ANFIS (mean absolute error: 0.4585) < Fuzzy-Rough Set Theory-ANFIS (mean absolute error: 0.5123). It shows that there are big problems in the indexes optimized by Fuzzy-Rough Set Theory. The accuracy of the predicted value and the true value of PSO-CS-ANFIS and AHP-Entropy weight-ANFIS is about 78%, and the prediction ability can be accepted. For the study of overall comfort in the standing state, we can use PSO-CS-ANFIS or AHP-Entropy weight-ANFIS model to predict, that is, we can use PSO-CS or AHP-Entropy weight optimization index to study the overall comfort in this state, that is, the best index combination to predict the overall comfort in the standing state is: group a: BM3 (bust), BM12 (elbow), BM15 (inside thigh), BM18 (knee); group b: BM12 (elbow), BM15 (inside thigh), BM18 (knee), BM19 (shank).

In jumping state, the average absolute errors of the four models are AHP-Entropy weight-ANFIS (average absolute error: 0.1372), fuzzy rough set theory-ANFIS (average absolute error: 0.3022), AHP-SEM-ANFIS (average absolute error: 0.5705), PSO-CS-ANFIS (average absolute error). It shows that the index optimized by PSO-CS-ANFIS has the highest accuracy in predicting the overall comfort in this state, that is, BM3 (bust), BM6 (abdomen), and BM19 (shank) are the best indexes for predicting the overall comfort in jumping state.

In squat state, the average absolute errors of the four models are AHP-Entropy weight-ANFIS (average absolute error: 0.1894), fuzzy rough set theory-ANFIS (average absolute error: 0.2035), AHP-SEM-ANFIS (average absolute error: 0.1535), PSO-CS-ANFIS (average absolute error). Although the average absolute error of AHP-SEM-ANFIS is the smallest, the average absolute error of PSO-CS-ANFIS is very close to it, so the optimization indexes of AHP-SEM and PSO-CS can be used to predict

the overall comfort of this state, that is, group a (BM5 (lumbar), BM7 (body side), BM8 (hip)) and group b (BM6 (abdomen), BM8 (hip), BM18 (knee)), respectively.

In squat down state, according to the average of absolute errors of the four models, we can know that the best models for index optimization are AHP-Entropy weight (average absolute error: 0.1527) and PSO-CS-ANFIS (average absolute error: 0.1772), that is, the best index combination for predicting the overall comfort in this state are respectively group a (BM6 (abdomen), BM8 (hip), BM18 (knee)) and group b (BM6 (abdomen), BM8 (hip), BM15 (inside thigh), BM18 (knee)).

In the jogging state, the average absolute errors of the four models are AHP-Entropy weight-ANFIS (average absolute error: 0.1217), AHP-SEM-ANFIS (average absolute error: 0.0945), PSO-CS-ANFIS (average absolute error: 0.1399), and the optimization indexes of these three models can be used as a whole in this state, but the indexes optimized by AHP-SEM are the best, namely BM8 (hip) and BM15 (inside thigh).

In the walking state, the minimum average absolute error is 0.1827, which belongs to AHP-Entropy weight-ANFIS model, that is, the best indicators for predicting the overall comfort in this state are BM2 (armpit), BM4 (back), BM9 (crotch), and BM15 (inside thigh). At this time, the average absolute error of PSO-CS-ANFIS is 0.2800, and the accuracy rate is 72%, which is an acceptable prediction level.

In the lifting legs state, the best model for predicting the overall comfort is PSO-CS-ANFIS (average absolute error: 0.1638), that is, the indexes optimized by PSO-CS are most suitable for predicting the overall comfort in the lifting legs state, and the indexes are BM8 (hip) and BM15 (inside thighs).

In the rest state, the better models for predicting overall comfort are PSO-CS-ANFIS (mean absolute error: 0.1471)

and AHP-Entropy weight-ANFIS (mean absolute error: 0.1848), that is, the indexes optimized by PSO-CS or AHP-Entropy weight model are suitable for predicting overall comfort in rest state, and the indexes are respectively: group a: BM4 (back), BM6 (abdomen), BM19 (shank); group b: BM2 (armpit), BM4 (back), BM6 (abdomen).

Generally speaking, the optimal prediction model of every motion state contains PSO-CS-ANFIS model, so the optimization index of PSO-CS could be used as the prediction of the overall comfort of all States. Secondly, AHP-Entropy weight-ANFIS model can be used to predict the overall comfort under most motion conditions. At the same time, PSO-CS and AHP-Entropy weight could be used to optimize the human body part indexes that affect the overall comfort.

Conclusion

According to the prediction results of every experiment state (i.e. standing, jumping, squat, squat down, jogging, walking, lifting legs, rest), Fuzzy-Rough Set Theory-ANFIS prediction model has the worst effect (i.e. the indexes optimized by Fuzzy-Rough Set Theory are the worst), and the other three models have their own advantages in every experiment state. Among them, PSO-CS-ANFIS model and AHP-Entropy weight-ANFIS model perform well, that is, PSO-CS and AHP-Entropy weight can be used to optimize the overall comfort prediction index in every experiment state.

There are great differences in the influence indexes of overall comfort in every movement state, that is, there are great differences in the comfort of human body parts. Therefore, when studying dynamic comfort, it is best to subdivide the movements and study the comfort in every movement state, which is not suitable for studying the whole movement state as an entirety.

In short, this study proposed a model which can obtain the comfort of every motion state without wearing experiments, which improves the research efficiency of the comfort of tights, and provides more accurate design basis for the comfort of tights and favorable technical guidance for maximizing the sports comfort, and finally realized that wearers could gain a better sense of movement when wearing tights and then improve their sport performance. The research methods of this study can be used to predict the comfort of every movement in other sports events.

Author note

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