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Design of a professional tap dance training path optimized based on intelligent algorithms

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Abstract Tap dance, as a dance form with distinctive rhythm and expressive power, has been widely used in dance professional courses. However, the traditional tap dance training methods have certain limitations, which make it difficult to provide accurate feedback on the quality of dancers' movements and training effects. In this study, an innovative tap dance movement training path was designed by introducing a leg movement recognition technique that combines an improved particle swarm optimization algorithm with support vector machine (SVM). First, wavelet threshold denoising and time-domain feature extraction are performed on the sEMG signals, and the parameters of the support vector machine model are optimized by combining the time-frequency combination features in order to improve the recognition rate of tap dance leg movements. The experimental results show that the average recognition rate based on the WL-MPF time-frequency combination features is 97.71%, which is significantly higher than that of the traditional single-feature recognition methods (e.g., the recognition rate of WL features is 95.85%). In addition, the experimental group performed significantly better than the control group in tap dance training, and the difference in total course performance was statistically significant (P<0.05). By introducing the intelligent leg movement recognition technology, the training path proposed in this paper can not only improve the accuracy of training, but also enhance students' interest in dance and improve the learning effect of dance movements. The method has high application value in tap dance teaching.

Index Terms tap dance, action recognition, particle swarm optimization algorithm, support vector machine, time-frequency combination features, intelligent training

I. Introduction

Dance major is a discipline with strong artistry, which is crucial for cultivating students' dance artistic literacy and professional ability [1]. And tap dance as an important branch of the dance major, the perfect training path has an important impact on the dance comprehensive quality such as the proficiency and professionalism of tap dance movements [2], [3].

As a unique dance form, tap dance has high technical requirements and expressive power, and in its movement training, it requires students to make more efforts to master [4], [5]. In the teaching process, the key is to stimulate students' interest in learning and focus on cultivating students' basic skills and teamwork consciousness [6]. At the same time, teachers need to reasonably adjust the teaching steps and content according to the actual situation of students, so that each student can receive appropriate guidance and assistance [7], [8]. This requires teachers to optimize the training strategy appropriately before carrying out teaching, and the optimization algorithm, as an important field of artificial intelligence, provides technical support for the realization of the path design of tap dance movement training [9], [10]. Optimization algorithms are mathematical and computational methods to find solutions that maximize or minimize a certain objective. Gradient descent algorithms and combinatorial optimization algorithms are the two main categories of optimization algorithms [11]. In tap dance movement training path design, optimization algorithms can not only realize the path design of tap dance movement training, but also provide students with personalized training paths, which improves the construction of dance majors through the integration of motion capture, path planning and other steps [12], [13].

This study proposes a leg movement recognition technique based on the combination of improved particle swarm optimization algorithm and SVM, which aims to accurately monitor and analyze dance movements in real time by intelligent means. Through the processing and analysis of sEMG signals, the method can effectively identify the dancer's leg movements, which in turn provides scientific feedback for training and helps the trainees optimize their movements to enhance the training effect. The core of the research is to apply the improved particle swarm optimization algorithm to the SVM model, optimize the parameters, improve the accuracy of movement recognition, and combine with the actual training needs to propose an innovative tap dance movement training path.

II. Specialization and development of tap dance movement training

II. A. Teaching the basics of the tap dance specialty

II. A. 1) Normative content of tap dance instruction

Rhythm is a kind of regular mutation in nature, society and human activities which is accompanied by rhyme. It is the source of the development of things, the soul of the beauty of all performing arts. Tap dance is the most representative of the rhythm as the soul of the art form.

The rhythm of tap dance is African rhythm - jazz rhythm (i.e. modern rhythm), which is the unique cultural inheritance inherited by African blacks. Rhythm is something that needs to be learned and practiced, and not everyone can do it just by feeling it. Therefore, the first thing to learn tap dance is to learn the core element of tap dance: rhythm.

Rhythm is the most important element in learning tap dance. Rhythm is made up of two elements: time and weight: the most basic rhythmic type is only 5 kinds (4 notes, 8 notes, swing 8 notes, 16 notes and triplets). The timing of the beats is the most important part of learning rhythm. With honest study and solid practice, the necessary foundation for rhythm is laid. Then you can begin to fill your heart with rhythm, gradually fill the gap in your heart for rhythm, so that the rhythm is deep inside, and your body and mind are rhythmically aligned and synchronized.

Tap dance steps are actually used as a vehicle to interpret rhythm, it has a strict linguistic structure, with its ABC letters and vocabulary dance steps, phrases, idioms and even chapters and poems, so “tap dance itself is music”. The combination of tap dance is a synthesis of all the elements of tap dance such as rhythmic knowledge, step system, and foot position, etc. Since it embodies all the elements of tap dance, it should be learned and mastered.

Improvisation is the essence of tap dance. The ultimate goal of learning tap is to be able to dance on the fly - improvisation - which is the ultimate goal of all dance. Improvisation is unprepared and tests the dancer's own dance quality and musical epiphany. Through improvisation, dancers can express their inner feelings and stimulate their creative potential. And in this process, the use of their own body language can accurately express the dancer's own understanding and interpretation of music [14], [15].

II. A. 2) Learning to read and use dance recording methods

The tap dance recording method is summarized and developed by the former according to the development law of tap dance combination and the correspondence between dance steps and music rhythm, which is the most scientific and effective recording tool for tap dance. It is the most scientific and effective recording tool for tap dance. It can accurately, standardize and completely record all the elements in the tap dance combination, and it can also be used for choreography and improvisation. When you record a complete combination with it, it actually becomes the dance sheet of tap dance. The score is the key to learning tap dance and an effective tool, just like the sheet music of the piano, which makes tap dance have a written record and inheritance and can be popularized all over the world. The recording of tap dance combinations is mainly about recording the three main elements of rhythm, steps and footwork.

II. B. The contemporary value of capacity building for dance majors in colleges and universities

(1) Requirements for high-quality development of higher education

Since the implementation of the “double first-class” construction of higher education, higher education has entered a new stage of development, promoting the rapid development of higher education. However, there is still a certain gap between higher education and the level of higher education in developed countries around the world. This requires all kinds of colleges and universities to seek common development, think deeply, and constantly improve the level of professional capacity building, promote the improvement of professional level, and realize the high-quality development of higher education.

The enhancement and construction of dance professional capacity in colleges and universities is an important issue under the strategic background of “double first-class” construction of colleges and universities. As an important part of higher education, through professional capacity enhancement and construction, we focus on the construction of dance majors, realize the construction of first-class disciplines, and promote the cultivation of excellent dance talents from the subdivision of majors. This is the inevitable experience of following the law of development of higher education and the inevitable requirement of the development of the times. Only by taking one step at a time, subdividing the construction and coordinating the planning can we practically realize the high-quality development of higher education.

(2) Requirements for sustainable development of students' career

The opening of the dance major is to cultivate excellent dance talents, and the professional construction process should first consider the ability and outlet of talents. From the students' point of view, the purpose of students learning dance is to hope for their own better development, to become excellent dance teachers or excellent dancers. Dance professional capacity enhancement and construction in colleges and universities should be student-centered, pay attention to students' comprehensive literacy training and professional level enhancement, in order to make students have core competitiveness and help students plan a good career future. Therefore, the enhancement and construction of college dance professional ability is the guarantee condition for students' career development and life prospect, and it is the basic requirement for students' sustainable development.

(3) Requirements of high level development of colleges and universities themselves

With the development of economic globalization and the advancement of global education integration, colleges and universities themselves are facing severe competition. On the one hand, the competitiveness of foreign colleges and universities is constantly improving, and many students choose to study abroad. On the other hand, the development of some local colleges and universities is not optimistic due to the influence of geography and local economy. This exacerbates the difficulties in the development of some colleges and universities. Therefore, the dance major, as a specialty offered by colleges and universities, starts from the enhancement and construction of professional ability, and keeps doing fine, fine, and strong to create the school's ace specialty. This is extremely favorable to the school's own high-level development. From the point of view of the development of colleges and universities, colleges and universities need to start from the subdivision of specialties, and constantly improve the capacity of professional construction, improve the quality of education and personnel training level. This can ensure that colleges and universities have a foothold in the competition in higher education.

II. C.Dance Science Training

Dance science training studies often use dance science as the main theory and methodology. The object of dance science research is the dancer's body and its dance movement performance. And the body is not just material at the medical level. It also carries psychological, emotional, social, cultural and many other aspects, and this multidimensional attribute makes it often reflect the complex movement of the “phenomenon of life”.

The main task of dance scientific training research is to explore the scientific theory and method of dance teaching and training. Such as in the analysis of the mechanics of dance movement technology, dancers body movement ability of the physiological factors affecting the dance action process of muscle work and nervous system regulation, dance training intensity and load, etc., based on the study of dance training movements and methods of innovative design or revision and improvement.

In terms of dance movement technology learning and training, some analysis of dance movements, such as anatomical basis, mechanical principles, technical key, movement structure characteristics and laws and other movement analysis research, for dance movement technology learning and training provides a scientific basis. Among them, in addition to the application of anatomy and mechanics for the theoretical level of analysis, it is worth paying attention to some research on the use of science and technology not only to realize the quantitative analysis of dance movement technology, but also to promote the external performance of the movement and its internal muscle work and strength and other biological and mechanical principles associated with the research trend. For example, the use of wearable devices such as heart rate telemetry and accelerometers for testing dance training loads and setting training intensity, the use of isokinetic technology for strength assessment and rehabilitation exercises, and the use of motion capture technology for dance movement image analysis and kinematic analysis.

III. Improved particle swarm optimization algorithm for leg action recognition

The overall framework of sEMG gesture recognition in this paper is shown in Fig. 1, including 3 parts: sEMG preprocessing, construction of feature classifiers, and recognition of gesture actions.

The sEMG preprocessing includes sEMG denoising and feature extraction. First, the original sEMG is denoised using wavelet thresholding. Second, the corresponding time-domain features are extracted from the sEMG of each type of gesture action, and the preprocessed sEMG time-domain features of each type of gesture action are used to fuse the improved particle swarm optimization algorithm with the support vector machine model training, which is used to find the optimization of the parameters C and σ in the SVM in order to build the final feature classifiers. Finally, the constructed classification model is used to recognize the gesture action.

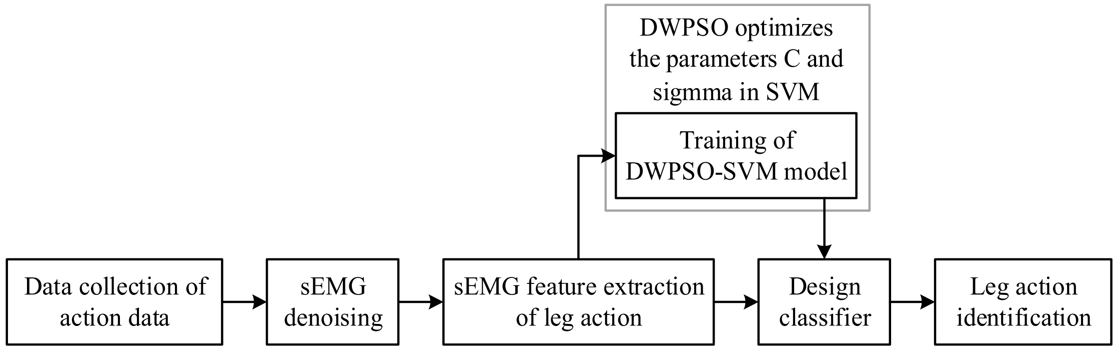

Figure 1: sEMG gesture recognition framework

III. A. sEMG preprocessing

III. A. 1) Wavelet thresholding denoising

In this paper, wavelet threshold denoising method is used to denoise the original sEMG.

Wavelet transform threshold denoising is based on wavelet transform, and Mallat algorithm is used to decompose the signal in multiple layers, after which thresholding will be done on the decomposed wavelet coefficients. After the above steps, the signal is then reconstructed. The process of wavelet reconstruction is to eliminate the signal, the wavelet coefficients that do not meet the requirements of the wavelet coefficients set to 0, so that do not meet the noise requirements of the signal will be set to 0, and not integrated into the reconstructed signal, in order to complete the noise reduction process.

The acquired original signal $x(i)$ is expressed in the following equation:

$$x(i) = s(i) + \sigma e(i), i = 0,1,\cdots,n-1 \tag{1}$$

where $x(i)$ is the signal containing noise. $s(i)$ is the signal that does not contain noise, $e(i)$ is the noise contained in the signal, and σ is the standard deviation of the noise.

The wavelet transform thresholding denoising method is divided into three steps in total:

Step1: Wavelet decomposition of the signal.

The wavelet decomposition of the signal is implemented using the Mallat fast algorithm, and the decomposition coefficients d of each layer of the wavelet can be obtained. I.e:

$$a_{i,j} = \sum_n h(n-2j)a_{i-1,n}, d_{i,j} = \sum_n g(n-2j)a_{i-1,n} \tag{2}$$

In the above equation, $h(n)$ denotes the low-pass filter and $g(n)$ is the high-pass filter. $a_{i,j}$ denotes the coefficients of the useful signal in the i th decomposition of the scale space. $d_{i,j}$ are the wavelet coefficients of the i th decomposition scale space. It is usually assumed that what exists in $cA_1, cA_2, \cdots, cA_n$ is the useful signal of the surface EMG signal, while $cD_1, cD_2, \cdots, cD_n$ is adulterated with the noise contained in the signal.

Step2: The process of thresholding.

After the calculation method of the threshold value will be determined, there is the choice of the threshold function, the traditional threshold function has a soft threshold function and hard threshold function.

Hard threshold function:

$$S_i(k) = \begin{cases} S_i(k) & , \quad |S_i(k)| > \lambda \\ 0 & , \quad |S_i(k)| \le \lambda \end{cases} \tag{3}$$

Soft Threshold Functions:

$$S_i(k) = \begin{cases} \operatorname{sgn}(S_i(k)) \,|\, S_i(k) - \lambda \,|, & |S_i(k)| > \lambda \\ 0, & |S_i(k)| \le \lambda \end{cases} \tag{4}$$

In the above two equations, $S_i(k)$ is the corresponding wavelet coefficient.

Step3: Wavelet reconstruction.

III. A. 2) Main feature segment extraction

Combined with the time of action completion during the experiment, the signal was divided into three segments: the start segment, the main feature segment, and the end segment.

The sEMG signal is divided into frames with a sliding window of 64 samples in increments of 32 samples, and the energy value of each frame is calculated, followed by an adaptive threshold th. This threshold is taken from the resting state signal and the energy value is rectified to obtain En. The value of En is counted when it is greater than th, and if three consecutive values of En are greater than th, the moment is judged to be the starting point of the signal. Let the signal be $X=\{x(1),x(2),x(3),...,x(N)\}$, where N is the sum of data lengths, the signal split-frame energy method is calculated as follows:

(1) Select the appropriate frame length and frame shift to split the signal into frames:

$$(M-1)\times I+L=N \tag{5}$$

where M is the total number of frames of the signal, l is the incremental frame step, L is the frame length, i.e., the length of the signal in each frame, and N is the total length of the signal. The signal after framing is obtained as $X'=\{x'(1),x'(2),...,x'(M)\}$, where $x'(1)=\{x(1),x(2),...,x(L)\},x'(2)=\{x(1+I),...,x(L+I)\}$.

(2) Calculate the total energy of each signal frame $En(i)$:

$$En(i)=\sum_{n}^{n+L}amp_{in}^{2} \tag{6}$$

where amp_n is the amplitude at the i th sampling point of the i th frame and $n\leq L$.

(3) Calculate the adaptive threshold th in terms of the signal energy during smooth standing:

$$th=\frac{\sum_{i=1}^{M}En(i)}{M} \tag{7}$$

(4) If En is greater than th in a certain frame, and is greater than th in the following 3 frames, then that frame is the start frame of the signal action segment.

(5) Intercept 2s of data after 0.5s of the start of the signal action segment to get the main feature segment signal. That is:

$$\begin{gathered}SN=(FS-1)\times F_s\\ MSN=SN+0.5\times F_s\\ MEN=MSN+2\times F_s\end{gathered} \tag{8}$$

where SN is the detected start point sampling point, FS is the number of start point frames, F_s is the sampling frequency, MSN is the sampling point 0.5s after the start point, and MEN is the sampling point 2.5s after the start point. then the signals from MSN to MEN are the main feature segment signals.

III. B. Principles of Support Vector Machines

Support Vector Machines (SVMs), a statistically based supervised learning algorithm, were first used to solve linear classification and later extended to solve nonlinear classification problems after kernel methods. The essential idea is to find a maximally spaced hyperplane to separate low dimensional data or original data mapped to higher dimensional data.

The given training data set T is as follows:

$$T=\{(x_1,y_1),(x_2,y_2),...,(x_N,y_n)\} \tag{9}$$

$x_i\in R'',y_i=\{-1,+1\},i=1,2,\cdots,N$. Converts the search for a maximally spaced separating hyperplane into an optimization problem containing constraints, i.e.:

$$\begin{aligned}&\min_{w,b}\quad \frac{1}{2}\|w\|^2\\ &s.t.\quad y(w\cdot x_i+b)-1\geq 0,i=1,2,...,N\end{aligned} \tag{10}$$

For linearly indivisible data for each sample point introduces a relaxation variable factor modifying the maximum interval hyperplane, at which point the optimization problem is:

$$\begin{aligned} &\min_{w,b} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \\ &s.t. \quad y(w\cdot x_i + b) \geq 1-\xi, i=1,2,...,N \\ &\qquad\ \ \xi_i \geq 0, i=1,2,...,N \end{aligned} \tag{11}$$

The corresponding decision function is:

$$f(x) = sign\left(\sum_{i=1}^{N} a_i^* y_i x_i x + b^*\right) \tag{12}$$

where C is the penalty coefficient, C determines the size of the penalty for misclassification, ξ represents the slack variable, used to adjust the interval between the sample points and the function. However, the above method can only solve linear classification problems, for nonlinear classification problems can not help, in order to make the SVM has the ability to classify nonlinear problems, the kernel function is added to the decision function, the use of the kernel function after the decision function is:

$$f(x) = sign\left(\sum_{i=1}^{N} a_i^* y_i K(x_i x) + b^*\right) \tag{13}$$

where $K(x_i x)$ is the kernel function. The Gaussian kernel function used for ECG classification maps the input feature space and the Gaussian kernel function is:

$$K(x_i x) = \exp\left(-\frac{\|x_1 - x_2\|^2}{2\sigma^2}\right) \tag{14}$$

III. C. Fundamentals of the Particle Swarm Algorithm

The Particle Swarm Algorithm (PSO) is inspired by the feeding behavior of flocks of birds, which is considered to be similar to the process of solving a mathematical optimization problem. Individual birds in a flock are equivalent to individual "particles" solving a mathematical problem, and the food that the flock searches for is also equivalent to the optimization of the optimal solution of the mathematical problem. In the process of searching for food (the optimal solution), each bird (particle) in the flock has to cooperate with each other as well as maintain competition in order to find the food (the optimal solution).

The optimization principle of the PSO algorithm is as follows: let there exist a population X in D-dimensional space, and the number of particles in X is n, then there is $X = (x_1, x_2, \cdots, x_n)$, and the position vector of the i-th particle individual can be expressed as $X_i = (x_{i1}, x_{i2}, \cdots, x_{ii})^T$, whose fitness value is determined by the objective function. The velocity vector of the i th particle can be expressed as $V_i = (v_{i1}, v_{i2}, \cdots, v_{i1})^T$, such that the individual optimal position is $P_i = (p_{i1}, p_{i2}, \cdots, p_{i1})^T$ and the population optimal location is $P_g = (p_{g1}, p_{g2}, \cdots, p_{gl})^T$. They both update their respective velocities and positions using the following iterative equations, which are:

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{gd}^k - x_{id}^k) \tag{15}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{16}$$

where k is the current number of iterations of the algorithm. ω is the inertia parameter, v_{id}^k and x_{id}^k are the velocity and position of the i th particle when the iteration number is k. v_{id}^{k+1} and x_{id}^{k+1} are the velocity and position of the i th particle when the iteration number is $k+1$. $d = 1, 2, \cdots, D; i = 1, 2, \cdots, n$, c_1, c_2 are the acceleration coefficients, r_1, r_2 are the stochastic functions, and $r_1, r_2 \in [0,1]$.

The PSO algorithm is simple in principle and can be operated strongly, but its optimization results are easily affected by the population size, acceleration coefficients and other parameters, improper parameter settings will affect the search ability of the particle swarm, the phenomenon of slow convergence or non-convergence, and sometimes there is a fall into the local minima.

III. D. Improved particle swarm optimization algorithm

In this paper, a new constraint factor α is introduced into the position update equation to constrain the influence weight of the current velocity on the current position update, and construct a new particle swarm algorithm, i.e., the dual-weight particle swarm algorithm. After introducing the constraint factor α the new position update Eq:

$$X_{ij}^{k+1} = x_{ij}^{k} + \alpha v_{ij}^{k+1} \tag{17}$$

The role of the constraint factor α is similar to that of the inertia weight $\tilde{\omega}$, the larger the value of α, the larger the change in X_{ij}^{k+1}, which favors the particle in global optimization. On the contrary, the smaller the value of α is, the smaller the change of X_{ij}^{k+1} is, which is favorable for the particle to find optimization locally.

For the updating of inertia weight $\tilde{\omega}$ and constraint factor α, this paper proposes an isotropic updating strategy, i.e., both inertia weight $\tilde{\omega}$ and constraint factor α are updated by decreasing strategy.
Combine DWPSO with the following four common weight updating strategies, take the updating formula of inertia weight $\tilde{\omega}$ as an example, and the updating formula of constraint factor α is the same as it.

(1) Linear update strategy, the linear decreasing strategy of inertia weight $\tilde{\omega}$ is shown in the following equation:

$$\tilde{\omega}^{i} = \tilde{\omega}_{start} - (\tilde{\omega}_{start} - \tilde{\omega}_{cnd})*(j/M) \tag{18}$$

and the value of $\tilde{\omega}_{start}$ is generally set to 0.6. The value of $\tilde{\omega}_{end}$ is generally set to 0.3.

(2) Nonlinear update strategy, the nonlinear decreasing strategy for the inertia weights $\tilde{\omega}$ is shown in the following equation:

$$\tilde{\omega}^{j} = \tilde{\omega}_{stant} - (\tilde{\omega}_{start} - \tilde{\omega}_{end})*(j/M)^2 \tag{19}$$

(3) Adaptive weighting strategy, the value of the weights is related to the value of the fitness function, the adaptive weighting strategy for the inertia weights $\tilde{\omega}$ is shown in the following equation:

$$\tilde{\omega}_i^j = \begin{cases} \tilde{\omega}_{start} - (\tilde{\omega}_{start} - \tilde{\omega}_{end}) \dfrac{f(x_i^j) - f_{\min}^j}{f_{avg}^j - f_{\min}^j}, f(x_i^j) \le f_{avg}^j \\ \tilde{\omega}_{end}, f(x_i^j) > f_{avg}^j \end{cases} \tag{20}$$

where f_{avg}^j is the average fitness of all particles at the jth iteration and $f_{\min}^j$ is the minimum fitness of all particles at the jth iteration, as follows:

$$f_{avg}^j = \sum_{i=1}^{N} f(x_i^i)/N \tag{21}$$

$$f_{\min^j} = \min\{f(x_1^j), f(x_2^j), \cdots, f(x_i^j)\} \tag{22}$$

(4) Stochastic weighting strategy with inertia weights $\tilde{\omega}$ The stochastic weight updating strategy is shown in the following equation:

$$\tilde{\omega}^{i} = \tilde{\omega}_{start} - (\tilde{\omega}_{start} - \tilde{\omega}_{end})*rand() + \sigma * randn() \tag{23}$$

where $rand()$ is a [0, 1] uniformly distributed random number. $rand()$ is a normally distributed random number, and the standard deviation is used to measure the degree of deviation between the weights of the random variable and its mean.

Support vector machine parameter flow for optimization based on two-weight particle swarm algorithm:

Step1: Assign random initial values to the velocity V_i and position X_i of each particle in the particle swarm and the penalization factor C and kernel function parameter σ in the SVM model.

Step2: Calculate the value of the fitness function, this paper adopts the error rate of SVM classification prediction as the objective function of fitness.

Step3: Calculate its individual fitness and population fitness for each particle in the population, if the current individual fitness function value is better than the individual historical optimal value, update the value of its individual optimal solution P_{best}. If the current population fitness function value is better than the global historical optimal value, update the value of its global optimal solution G_{best}.

Step4: Update the inertia weight $\tilde{\omega}$ and the constraint factor α according to the weight updating strategy, and update the velocity and position of the particle using Eq.

Step5: If the location of the optimal solution is found or the maximum number of iterations of the population is reached, the algorithm terminates. Otherwise, go to Step2 and continue the parameter optimization search.

Step6: Output the optimal penalty factor $best.C$ and optimal kernel function parameters $best.\sigma$ found by the improved particle swarm optimization algorithm, so as to build the optimal SVM classification model.

III. E. Tap Dance Movement Training Practices

III. E. 1) Tap Dance Movement Recognition

In this paper, 5 kinds of time domain features and 2 kinds of frequency domain features are linearly combined in pairs to synthesize 10 kinds of time-frequency combination features as new gesture recognition features.

The five time domain features extracted in this paper are: slope change number (SSC), absolute mean (MAV), root mean square (RMS), variance (VAR), and waveform length (WL).The two frequency domain features are: mean power frequency (MPF), and median frequency (MF).

In this paper, 10 kinds of time-frequency combination features are proposed: SSC-MPF, MAV-MPF, RMS-MPF, VAR-MPF, WL-MPF, SSC-MF, MAV-MF, RMS-MF, VAR-MF, WL-MF.

(1) Recognition of tap dance leg movements based on a single feature

In this paper, five time-domain features, two frequency-domain features, and one time-frequency-domain feature are selected as classification features respectively, and the SVM classifier after optimizing the parameters by PSO is used to recognize 10 classes of tap dance leg movements.

The average recognition rate of the subjects for the 10 classes of tap dance leg movements is shown in Figure 2. As can be seen from the figure, for the time domain features, the average recognition rate of tap dance leg movements based on WL features is the best, which is 95.85%. For frequency domain features, the average recognition rate of tap dance leg movements based on MPF features and the average recognition rate of tap dance leg movements based on MF features are 90.74% and 81.19%, respectively.

It can be seen that the average recognition rate of tap dance leg movements with single time-domain feature and single frequency-domain feature are not high. Therefore, the classification effect of selecting single time domain or frequency domain features as the features for tap dance leg movements recognition is not ideal.

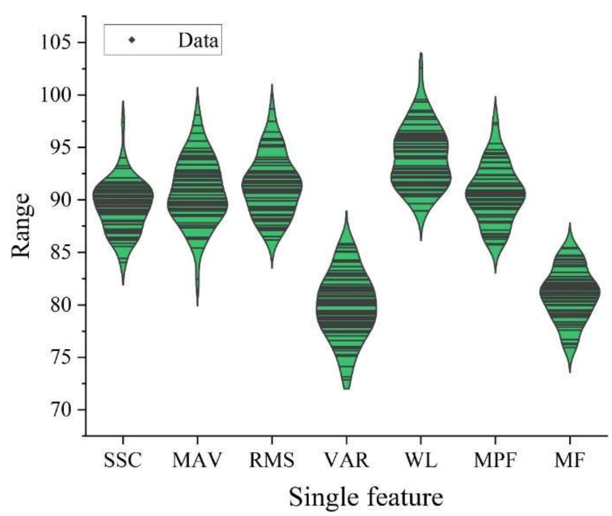

Figure 2: The average recognition rate for 10 types of tap dancing legs

(2) Recognition of tap dance leg movements based on time-frequency combination features

In this paper, 10 kinds of time-frequency combination features are selected as classification features, and the average recognition rate of tap dance leg movements of time-frequency combination features is shown in Fig. 3. The figure shows the average recognition rate of tap dance leg movements based on 10 kinds of time-frequency combination features.

Among the average recognition rates of tap dance leg movements based on multiple time-frequency combination features, the average recognition rate based on WL-MPF time-frequency combination features is the highest, which is 97.71%. It was followed by RMS-MPF (97.29%) and MAV-MPF (97.18%) in that order. So the average recognition rate of time-frequency combination features has been improved more significantly compared to the average recognition rate of single features.

In order to improve the accuracy of tap dance leg movement recognition, this paper proposes a PSO-SVM leg movement recognition method based on time-frequency combination features to recognize and classify multiple tap dance leg movements.

The results show that the time-frequency combination features WL-MPF, RMS-MPF, and MAV-MPF have better gesture recognition rates relative to its corresponding time-domain features and frequency-domain features. It can be seen that the PSO-SVM recognition method based on the time-frequency combination features WL-MPF, RMS-MPF, and MAV-MPF has good classification effect for tap dance leg movement recognition.

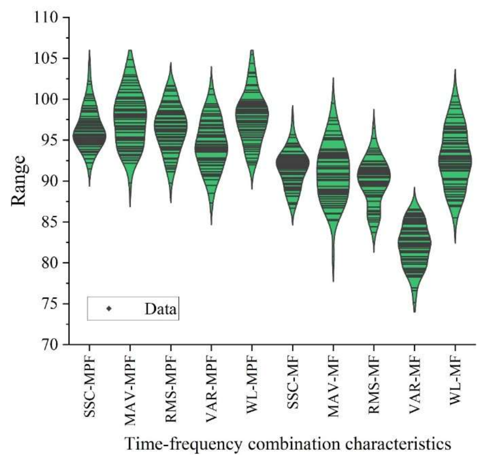

Figure 3: The average recognition rate of the leg action of the band feature

III. E. 2) Tap Dance Movement Training

The questionnaire was divided into student questionnaire and teacher questionnaire, in which the student questionnaire was divided into pre-test and post-test questionnaires of the experiment, each of which was 45, with a validity rate of 100%. Teachers' questionnaires were distributed 6 copies, with an effective rate of 100%.

In this paper, in XX University 2024 grade undergraduate, 2 teaching classes of undergraduate students were randomly selected as experimental subjects, experimental students have no history of major diseases, have not used drugs that affect the stability of the body, and agreed to participate in this experiment.

The experiment was conducted in the form of experimental and control groups, and the experimental groups were randomly generated in order to ensure that the experiment was scientific and precise. The two groups use the static technical exercises of tap dance selected by experts combined with intelligent leg movement recognition to carry out tap dance leg movement special exercises.

The control group carries out normal dance teaching content learning according to the syllabus. The total learning time was 5 weeks, 2 hours per week, 10 lessons in total. During this period, the students' mastery of dance movements was recorded, and at the end of the final course, the mastery of dance movements of the two groups of students was analyzed and demonstrated to prove whether tap dance static technique practice combined with intelligent leg movement recognition for tap dance leg movement special practice can help tap dance movement training, and thus a feasible path was proposed.

Experiment time: March 18th, 2025-April 19th, 2025

Place of experiment: Dance classroom of XX University

The difference between the final grades of the courses of the students in the experimental group and the control group can intuitively reflect the quality of teaching, due to the fact that there is no difference in the basic quality conditions of the students in the two groups of classes. Through the comparative analysis of course scores, the influence of incorporating intelligent leg movement recognition on tap dance movement training can be obtained.

There are three main indicators for course scoring, which are students' body posture (30 points), musical and artistic expression (30 points), and dance movement completion (40 points), with a total course score of 100 points.

The final course scores of the experimental group and the control group are shown in Table 1. By comparing the final course scores of the experimental group and the control group, $P<0.05$ indicates that there is a significant difference between the class scores of the two groups. The final course scores of the experimental group were better than those of the control group, indicating that the incorporation of intelligent leg movement recognition helps the implementation of tap dance movement training.

Table 1: Final results of the experimental group and the control group

	Control group	Experimental group	F	t	p
Physical posture	22.75±2.39	26.87±2.04	5.788	-10.513	0.008
The expression of music and art	24.64±4.19	27.04±3.55	3.504	-8.779	0.014
Completion of action	31.02±5.57	34.91±3.29	2.669	-6.225	0.001
Course performance	78.41±6.27	88.82±4.24	5.037	-8.001	0.000

This part is investigated and researched by means of questionnaires to the class students after the experiment. Through the feedback of students' satisfaction with the classroom content of tap dance movement special training can summarize whether the current teaching content of dance majors is reasonable or not, the questionnaire situation of the experimental students will be compared and analyzed to summarize what kind of influence the integration of intelligent leg movement recognition has brought to the rationalization of the teaching content of tap dance movement.

The students' interest in tap dance dance before and after the experiment is shown in Table 2. The Likert score was used as a benchmark for the teaching evaluation of tap dance movement-specific training.

The interest of the students in the control group and the experimental group in tap dance before the experiment was mainly focused on general. Through 5 weeks of study and training, the students' interest options migrated toward interest, and the vast majority of students were interested in learning tap dance dance. At the same time the number of students who were not interested before the experiment decreased in both classes. This reflects that the students' interest in learning tap dance has changed for the better in the tap dance classroom that incorporates the intelligent leg movement recognition technology practice. Therefore, this paper proposes a new tap dance movement training path, that is, based on the improved particle swarm optimization algorithm and SVM algorithm fusion of the leg movement recognition technology, the technology is incorporated into the tap dance movement special training, to enhance the professional degree of tap dance movement training.

Table 2: Students' interest in tap dance dance before and after the experiment

Scoring	Experimental group		Control group	
	Before the experiment	After the experiment	Before the experiment	After the experiment
5(Very interested)	18	22	13	14
4(Be interested in)	12	12	10	11
3(OK)	9	11	15	14
2(Not very interested)	4	0	3	3
1(Disinterest)	2	0	4	3

IV. Conclusion

According to the experimental results, the tap dance movement training path based on the fusion of the improved particle swarm optimization algorithm and the support vector machine significantly improves the recognition accuracy of tap dance leg movements. In the comparison between the experimental group and the control group, the experimental group showed better performance than the control group in terms of dance movement completion, artistic expression and body posture, and the difference in the final total course score reached a significant level ($P<0.05$), which proved the positive impact of the intelligent leg movement recognition technology on tap dance movement training. In particular, after using the WL-MPF time-frequency combination of features, the accuracy of tap dance movement recognition was increased to 97.71%, which far exceeded the recognition effect of a single feature. It can be seen that combining intelligent technology with tap dance movement training not only improves the training efficiency, but also effectively helps students make more progress in the mastery and performance of dance movements. This research provides strong support for the technological innovation and training mode reform in dance professional education.

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