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Analysis of Quantum Evolutionary Genetic Algorithm for Optimizing the Path of Physical Education Teachers' Professional Development and Teaching Ability Improvement in the Information Age

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Abstract Aiming at the fundamentals and importance of sports action technology, combined with the existing development of sports action image recognition and analysis technology, this paper introduces the corner mechanism of quantum revolving door into the quantum genetic algorithm, and proposes the gradient-based adaptive quantum genetic algorithm. Using bilinear interpolation method to geometrically transform the sports action images, combining the normalized interrelationship measure with the improved quantum genetic algorithm to realize the sports action image matching process. To statistically compare the performance of the improved quantum genetic algorithm with other algorithms for sports action image segmentation. Analyze the total mean scores of teaching ability of sports trainee teachers when using quantum genetic algorithm to adjust sports movement techniques. In the function test, the improved quantum genetic algorithm adopts the quantum gate adaptive rotation angle strategy, which can avoid algorithm divergence or premature convergence, improve the accuracy and speed of algorithm optimization, and make the algorithm more robust. The total mean scores of teaching ability of physical education trainee teachers in the initial stage and the end stage of the internship were 3.49 and 4.45 respectively. The difference of the total mean scores of teaching ability proved the feasibility of the image matching technique of quantum genetic algorithm for the improvement of movement skills and the enhancement of teaching professionalism of physical education teachers.

Index Terms quantum genetic algorithm, normalized inter-correlation, sports movement images, teaching ability

I. Introduction

In the context of the information age, education informatization has become an important force to promote the modernization of education [1], [2]. School physical education is an important part of comprehensive quality education, and it is even more important for students' physical and mental health development [3], [4]. The physical education teacher is the implementer of physical education, whose professional level and teaching quality directly affect the effectiveness of school sports [5]. In recent years, although the overall quality of the physical education teachers' team has been improved, there are still some problems, such as slow updating of professional knowledge, outdated teaching concepts, and single teaching methods, which affect the effective development of school sports [6]-[8]. Therefore, it is particularly important to deeply improve the effective path of professional development and teaching ability enhancement of school physical education teachers.

With the gradual deepening of the information age and education reform, the integration of information technology into physical education has become a major change in teaching today [9], [10]. Multimedia information technology, as a new form of education and modernized teaching means, is bound to have a great impact on traditional education [11], [12]. And as physical education teachers grow older and their own professional qualities continue to deteriorate, they can no longer be better adapted to modern education and teaching [13], [14]. Information technology as a tool, medium and method into the various levels of teaching, not only can improve the efficiency of teaching and learning, improve the effect of teaching and learning, change the traditional teaching mode, but also can further enhance the professional development of physical education teachers, laying the foundation for the effectiveness of classroom teaching [15]-[18]. In addition, modern information technology also provides teachers with a huge amount of teaching resources, including lesson plans, teaching courseware, teaching videos and so on [19], [20]. Teachers can utilize these resources to conduct diversified teaching activities to meet the needs of different students [21]. In addition, with the help of the Internet and online education platforms, teachers can communicate and share their teaching experiences with other teachers and experts, so as to continuously improve their teaching ability [22]-[24].

In this paper, combining the basic professional requirements of physical education teachers in the era of information technology and the new requirements including the transformation of personalized teaching concepts, we try to put forward the implementation path of using information technology to improve the professional development of physical education teachers. Based on the existing development of sports action image recognition, the quantum genetic algorithm is improved and an image matching technique based on the improved quantum genetic algorithm is formulated. The technology is brought into four types of sports classical action images for the calculation of average maximum entropy, average number of generations, and average time indexes to analyze the advantages of the algorithmic technology. Physical education trainee teachers were invited to participate in the teaching experiment, and the total average scores of the teaching ability of the physical education trainee teachers at the initial stage of the internship and at the end of the internship were recorded and compared.

II. Foundations and realities of professional development enhancement

II. A.Basic professional requirements

(1) Mastering multi-disciplinary knowledge

As an important role in the field of education, physical education teachers not only need to have specialized physical education skills and knowledge, but also need to master multidisciplinary knowledge in order to better perform their duties. First of all, physical education teachers need to have solid physical education skills and knowledge, including skills and theoretical knowledge of various sports. In teaching practice, physical education teachers need to be able to teach a variety of sports, such as soccer, basketball, track and field, and swimming, and to be able to explain relevant techniques and tactics. Secondly, physical education teachers need to understand the basic principles and methods of sports training, including nutrition, recovery and injury prevention for athletes. In order to better protect the safety of teachers and students in physical education, physical education teachers also need to understand the relevant safety knowledge of sports training, as well as the treatment and solution measures for physical injuries caused in the process of sports training. Finally, physical education teachers need to master effective teaching methods and strategies, including how to stimulate students' interest, how to organize classroom activities, how to assess students' learning outcomes, etc. They should also be able to adapt to the needs of different students, tailor the teaching to the needs of different students, and adopt appropriate teaching methods. In addition to physical education skills and knowledge, physical education teachers also need to have knowledge of other disciplines, such as health, nutrition, psychology, sociology, etc., which can help physical education teachers better understand the needs of students and provide a more comprehensive education [25].

(2) Possessing a healthy body and abundant energy

Physical education teachers can effectively instruct students in physical exercise and promote their physical and mental health only if they have a healthy body and abundant energy themselves.

On the one hand, a healthy body is a basic requirement as a physical education teacher, because physical education teaching is not only teaching knowledge and skills, but also need to participate in sports activities with students, the physical education teacher's physical quality directly affects the quality of teaching. If the physical education teacher's own physical quality is poor, it will be difficult to lead students in professional sports training, and it will be difficult to give students a good example, which will ultimately affect the quality of education and teaching.

On the other hand, abundant energy is the key to ensure the quality of teaching. Physical education teachers need to be able to maintain a high degree of concentration for a long time, deal with complex physical education teaching tasks, and also need to cope with unexpected situations, so abundant energy is essential. Physical education teachers need to have a high sense of responsibility and dedication. Physical education teachers need to love the cause of physical education, be responsible for students, pay attention to students' physical and mental health, and actively guide students to establish the correct values of physical education and healthy lifestyles.

II. B.New requirements

Artificial intelligence has brought convenience to the professional development of physical education teachers, but it has also put forward new requirements for physical education teachers. These requirements involve many aspects of physical education teaching, such as content, objectives, and methods. Among them, several aspects, such as personalized teaching, data-driven teaching, technology application ability, and educational ethics, are the most serious and urgent issues facing physical education teachers.

II. B. 1) Changes in the concept of personalized instruction

In the era of artificial intelligence, personalized teaching will become the most characteristic way of physical education. Each student is a unique individual with different physique, personality and ability. The emergence of artificial intelligence can help physical education teachers accurately collect information about each student and design exclusive classroom programs and training methods for them.

However, the current concept of holistic teaching and holistic practice in physical education classes has taken root in people's minds, and many physical education teachers have become accustomed to teaching on a class or even grade level basis. This traditional teaching method focuses on collective activities and overall coordination, and develops students' basic sports literacy and teamwork spirit through unified teaching content and practice programs. In this model, teachers are able to efficiently organize large-scale teaching and learning activities to ensure that all students are able to participate in unified physical education training.

However, the model of holistic teaching also has its limitations. In actual teaching, each student has different physical fitness, athletic ability and interests, and it is usually difficult for a unified teaching content to meet the needs of all students. Some students with better physical fitness feel that the intensity of training is insufficient, while those with weaker physical fitness cannot keep up with the progress, and this variability may affect their motivation to participate and their learning effectiveness.

In addition, the traditional holistic teaching model is also difficult to adjust to the special needs of individual students, and cannot give full play to the potential of each student. Therefore, in the era of artificial intelligence, it is a new challenge for physical education teachers to shift their teaching attention from the whole to the combination of the whole and the individual to form a more flexible and personalized teaching mode. Through artificial intelligence technology, teachers can more accurately understand the situation of each student and formulate a teaching plan that is more in line with their actual needs, thus realizing personalized teaching and improving the quality and effect of physical education.

II. B. 2) Data-driven instruction

Data-driven instruction is an instructional approach that utilizes data analysis to make instructional decisions and guide practice. It relies on student learning data so as to provide an objective picture of students' learning needs, progress and problems. This approach enables teachers to personalize the content and methods of instruction to more effectively support student learning based on student data.

Through the data-driven teaching approach, teachers can more accurately assess the effectiveness of teaching and learning, identify students' learning difficulties in a timely manner, and adopt appropriate teaching strategies and interventions. This not only helps to improve students' academic performance, but also promotes continuous improvement and optimization of the teaching and learning process.

However, this teaching method has certain requirements for physical education teachers. Because the data-driven teaching method relies on a variety of student data, physical education teachers need to have a certain data collection ability as well as the ability to analyze data in order to effectively understand the individual differences in students' athletic performance, skill level, and physical fitness status.

II. B. 3) Capacity for technology application

Improving technology application ability has become one of the abilities that physical education teachers must have in the new era and new stage. To improve the ability to apply technology, physical education teachers need to continuously strengthen their own artificial intelligence literacy, master in-depth knowledge in the field of artificial intelligence, and expand their theoretical knowledge of disciplines related to artificial intelligence. This includes an in-depth understanding and research on the basic principles of AI technology, its development trend and its application in sports teaching and training. At the same time, physical education teachers should also continue to expand their knowledge of disciplines related to artificial intelligence, such as computer science, data science, and equipment applications, in order to better apply advanced technological means to support teaching practice and continuously improve the level of teaching and quality of service.

III. Proposed information technology-based professional development path for physical education teachers

III. A. Image-based sports action recognition and analysis

III. A. 1) Technical Motion Image Processing

(1) Picture input is the pre-preparation work for base stuff analysis, which is mainly realized through two types of media: one is to input the original static pictures into the computer through scanner equipment. The other is to utilize photographic and photographic equipment to take actual pictures of the sports trainers and then input them into the computer for preprocessing.

(2) The pre-processing of the image is to process and repair the object using image editing software such as Photoshop, which removes stray colors and dots in the image, as well as sights that are not related to the action. If the image is blurred and not clear enough, the image needs to be scaled appropriately to ensure that its resolution and size are consistent. Some backgrounds, invisibility and human facial expressions in the image will bring some difficulty and complexity to the human frame recognition processing, and it is necessary for the operator to sharpen them accordingly. Through the software, the outline of the image on the line to modify the filling, presenting a clear edge, highlighting the edges and contours of the figure of these linear elements, while reducing other factors that will have an impact on the picture recognition.

(3) Quantitative processing mainly contains:

First, based on the image templates and limb constraints in the human model library, the limb search needs to follow the head-down approach, so as to determine the joints and the absolute position of each limb.

Second, the relative position data of the limbs are calculated to determine the motion data of the limbs.

Third, the key body shapes are represented by the method of characteristic limb representation.

Fourth, the relevant descriptions of key body shapes, transition times, coding, and movement trends are stored in the technical movement model library.

III. A. 2) Analysis of technical movement patterns

Pattern analysis of technical movements is an important process of computer technology in sports technical movement processing technology, based on the standard movements and human body structure modeling, to establish the technical movement model. The working process of technical movement pattern analysis is to compare the human body's specified movements with the standard movements in the computer, to draw corresponding reports and conclusions, and then form the movement model library. For the action model library covers more content and has certain operational functions, we will be related to the sports action into the library, the library of action search, can be statistical action characteristic parameters and a series of applications.

III. B. Quantum Genetic Algorithm

Quantum Genetic Algorithm (QGA) is the most representative quantum evolutionary algorithm, which was first proposed to introduce quantum state coding into evolutionary computation, and started human research on quantum genetic algorithms. In traditional evolutionary algorithms, populations are updated using crossover and mutation operations, while QGA proposes to update quantum chromosomes using quantum revolving door operations. Population optimization is carried out by checking the table to determine the updating method of rotating angle, the main parameters in the table include the quantum chromosome changes and fitness function values during the evolution of the population.QGA outperforms the traditional genetic algorithms in terms of convergence speed and global search performance [26], [27].

The execution steps of quantum genetic algorithm are:

(1) Initialize the quantum chromosome population

Denote the population containing n individuals as $Q(t)=\left\{q_1^t,q_2^t,q_3^t,\cdots,q_n^t\right\}$, where $q_j^t\left(j=1,2,\cdots,n\right)$ is the t th quantum chromosome of the population. Generation j quantum chromosome. The initial value of the quantum bit probability amplitude for each individual in the population is set to $\left(\alpha_i,\beta_i\right)=\left(\frac{1}{\sqrt{2}},-\frac{1}{\sqrt{2}}\right)\left(i=1,2,\cdots,m\right)$. Set the number of iterations $t=0$.

(2) Quantum observation

Conduct one observation for each individual in the population $Q(t)$, the observation process is carried out bit by bit, the quantum observation means to randomly generate a random number between $[0,1]$, if the random number is less than the probability amplitude, the measurement result is taken as 0, otherwise, it is taken as 1. The quantum coding will be converted into a binary coding string after this step. The observation $P(t)=\left\{p_1^t,p_2^t,\cdots,p_n^t\right\}$, where $p_j^t\left(j=1,2,\cdots,n\right)$, n is the population size, and m is the length of the quantum chromosome.

(3) Calculate the value of the degree of adaptation and save the optimal

The binary number obtained after observation is converted to decimal number in turn, and brought into the objective function for calculation, to find the fitness value of the objective function, this value is the fitness value. Save the maximum value of all the fitness values and the solution of the function that obtains the maximum value.

(4) Quantum update

The main function of quantum update is to change the state of quantum bits of quantum chromosome in the previous generation through continuous iteration to increase the probability of producing good binary individuals and realize the evolution of quantum chromosome.

Using quantum gate transformation matrix to update the population, according to the reversibility of quantum gate transformation matrix, choosing different quantum gate transformation matrices can effectively solve the application problem. The commonly used quantum gate transformation matrices are quantum rotating gate, heteroscedastic gate, controlled heteroscedastic gate, and so on.

Quantum genetic algorithm is a probabilistic optimization search algorithm derived from genetic algorithm. It not only preserves the advantages of genetic algorithm, but also fills the shortcomings of genetic algorithm. In many researches, quantum genetic algorithm has faster convergence speed, good optimization searching ability, and performs better than traditional methods in solving optimization problems. Other properties present in the algorithm are: small population, only a small number of populations are required to be able to complete the computation. Genetic algorithm decreases the diversity of the population in the later stages of the algorithm execution, but QGA algorithm has a diverse and rich population and hence has a better global searching ability as compared to the genetic algorithm. A quantum bit can represent many states and each individual has little interrelationship with each other, which reduces the required solution time in terms of time.

Summarizing the many advantages of quantum genetic algorithms in theoretical research, there are also the following disadvantages: in the traditional QGA algorithm, quantum revolving door operation in the selection of the rotation angle is generally a fixed value. There are many parameters that need to be set by looking up the table, and the flexibility of the angle is limited with the continuous evolution of the population, which is easy to make the convergence speed of the population change. Moreover, the iterative goal of the QGA algorithm is the current optimal solution, so that as the population continues to evolve it may affect the algorithm's ability to find the optimal solution, causing it to fall into the local extremes and affecting the final result. Therefore the research and improvement of quantum genetic algorithm is necessary.

III. C. Gradient-based adaptive quantum genetic algorithm

In this chapter, a new adaptive-based computational method is proposed by combining the cornering mechanism of quantum revolving door with the gradient of the objective function, and then an improved quantum genetic algorithm (GQGA) is proposed based on this method.

(1) Coding scheme

In the improved quantum genetic algorithm, the encoding is mainly realized by the corresponding probability amplitude on the quantum bits. When encoding, two aspects are considered, the condition that the probability amplitude corresponding to the quantum state must follow, and the stochastic characteristics of the initial population encoding. Based on this, it is more appropriate to choose the double chain coding method as follows:

$$p_i = \begin{bmatrix} |\cos(t_{i1})| & |\cos(t_{i2})| & \cdots & |\cos(t_{in})| \\ |\sin(t_{i1})| & |\sin(t_{i2})| & \cdots & |\sin(t_{in})| \end{bmatrix}, i = 1,2,\cdots,m, j = 1,2,\cdots,n \tag{1}$$

In the above equation, n denotes the number of quantum bits, m denotes the size of the population, $t_{ij} = 2\pi \times rand$, and $rand$ is a random number between 0 and 1. In the GQGA algorithm, the probability amplitude corresponding to each quantile can be treated as if it were two juxtaposed genes, then the two juxtaposed gene strands are contained in a chromosome, and the optimal solution can then be represented by any one of the gene strands. This allows each chromosome to be searched for both optimal solutions in the space at the same time. As follows:

$$p_{ic} = \left(\cos(t_{i1}), \cos(t_{i2}), \cdots, \cos(t_{in})\right) \tag{2}$$

$$p_{is} = \left(\sin(t_{i1}), \sin(t_{i2}), \cdots, \sin(t_{in})\right) \tag{3}$$

In the above equation, $i = 1,2,\cdots,m$, p_{is} means "sine" solution, p_{ic} means "cosine" solution. This operation not only eliminates the need for binary and decimal conversion, but also eliminates the random errors associated with measurements. The efficiency of the algorithm is enhanced by the fact that both the sine and cosine solutions are updated simultaneously in each evolutionary generation, thus enhancing the search traversability of the solution space. In addition, the number of globally optimal solutions can be guarded, which in turn leads to a larger increase in the probability of obtaining the globally optimal solution.

(2) Solution Space Transformation

In each population, there are $2n$ quantum bits of probability amplitudes in each chromosome, and the n-dimensional unit space $I^n = [-1,1]^n$ of these $2n$ probability amplitudes is mapped to the solution space Ω of the optimization problem Eq. (5) by applying a linear transformation. Each probability amplitude corresponds to one optimization variable in the solution space. Denote the i th quantum position on chromosome p_j as $[\alpha_i^j, \beta_i^j]^T$, and the corresponding solution space variable is:

$$X_{ic}^j = \frac{1}{2}\left[b_i\left(1+\alpha_i^j\right)+\alpha_i\left(1-\alpha_i^j\right)\right] \tag{4}$$

$$X_{is}^j = \frac{1}{2}\left[b_i\left(1+\beta_i^j\right)+\alpha_i\left(1-\beta_i^j\right)\right] \tag{5}$$

(3) Determination of Quantum Revolving Door Turning Angle

In the improved quantum genetic algorithm, the quantum rotating gate is used to update the quantum bit phase with the expression:

$$U(\Delta\theta) = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \tag{6}$$

The update process is:

$$\begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \cos(t) \\ \sin(t) \end{bmatrix} = \begin{bmatrix} \cos(t+\Delta\theta) \\ \sin(t+\Delta\theta) \end{bmatrix} \tag{7}$$

The method of determining the size of the corner of a quantum revolving door can be described as follows: by analyzing the trend of the change of the objective function at a particular chromosome, followed by the calculation of the corner step size using this change information. The rate of change of the objective function at the chromosome search point determines the size of the corner step, and when this rate of change is small, the corner step can be increased. When the rate of change is large, the corner step size can be reduced. In this way, not only the speed of convergence is improved, but also the global convergence is not adversely affected. According to the above description, the corner step function can be constructed as follows:

$$\Delta\theta_{ij} = -\operatorname{sgn}(A) \times \Delta\theta_0 \times \exp\left(-\frac{\left|\nabla f(X_i^j)\right| - \nabla f_j \min}{\nabla f_j \max - \nabla f_j \min}\right) \tag{8}$$

$\nabla f_j \min$ are defined as:

$$\nabla f_j \max = \max\left\{\left|\frac{\partial f(X_1)}{\partial X_1^j}\right|, \cdots, \left|\frac{\partial f(X_m)}{\partial X_m^j}\right|\right\} \tag{9}$$

$$\nabla f_j \min = \min\left\{\left|\frac{\partial f(X_1)}{\partial X_1^j}\right|, \cdots, \left|\frac{\partial f(X_m)}{\partial X_m^j}\right|\right\} \tag{10}$$

$$A = \begin{vmatrix} \alpha_0 & \alpha_1 \\ \beta_0 & \beta_1 \end{vmatrix} \tag{11}$$

(4) Quantum crossover operation

Quantum Genetic Algorithm (QGA) has been used to solve combinatorial optimization problems with good results. However, when the optimization of continuous functions is handled by QGA, the result is prone to the phenomenon of “early maturity” because the crossover operation is not used in the operation process.

In this chapter, a new quantum crossover operation, i.e., full perturbation crossover, is created by utilizing the coherence of quantum. In this crossover operation, all chromosomes in the population are involved in the operation.

(5) Mutation Processing

In improved quantum genetic algorithms, the mutation operation of chromosomes is generally realized by quantum nongate to the mutation probability. Any one individual chromosome, followed by any number of quantum bits, is selected and subjected to a quantum non-gate transformation such that the two probability amplitudes of that quantum bit are transformed with respect to each other. The purpose of such an operation is to enable both gene strands to be mutated simultaneously. In fact, this mutation operation is a rotational operation on the quantum bit amplitudes. This operation both ensures the diversity of the population and reduces the probability of premature convergence of the population. As in the case of the mutation strategy based on the single-bit quantum Hadamard, the effect of the gate is:

$$\frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}\begin{bmatrix}\cos(\theta_{ij})\\ \sin(\theta_{ij})\end{bmatrix}=\begin{bmatrix}\cos\left(\frac{\pi}{4}-\theta_{ij}\right)\\ \sin\left(\frac{\pi}{4}-\theta_{ij}\right)\end{bmatrix} =\begin{bmatrix}\cos\left(\theta_{ij}+\frac{\pi}{4}-2\theta_{ij}\right)\\ \sin\left(\theta_{ij}+\frac{\pi}{4}-2\theta_{ij}\right)\end{bmatrix} \tag{12}$$

where $i\in\langle 1,2,\cdots,m\rangle$, $j\in\{1,2,\cdots,n\}$, it is not difficult to realize from the above equation that this mutation strategy is essentially a kind of rotation, which makes it very easy to compute the chromosome i on the The size of the corner of the j th quantile, which is $\Delta\theta_y=\pi/4-2\theta_y$, enhances the diversity of the population.

III. D. Image matching based on improved quantum genetic algorithm

In image matching, the use of simple traversal search results in a huge amount of computation, and heuristic intelligent optimization algorithms such as Quantum Genetic Algorithms can effectively reduce the number of search points and thus improve the accuracy and speed of the search.

In this chapter the image matching process will be implemented using the proposed normalized correlation measure (NCC) and improved quantum genetic algorithm. Firstly, the basic process of image matching is briefly introduced, then the focus is on the scheme and steps of implementation, and finally the experimental simulation is carried out.

III. D. 1) Normalized Mutual Correlation Matching Algorithm

The Normalized Correlation (NCC) matching algorithm belongs to the region-based grayscale matching and is a commonly used method in image feature matching.

$$\cos\theta=\frac{\vec{a}\cdot\vec{b}}{|\vec{a}|\cdot|\vec{b}|} \tag{13}$$

If the value of $\cos\theta$ is close to 1, it means that the angle between the vector $\vec{a}$ and the vector $\vec{b}$ is close to 0 degrees, then the two vectors are in the same direction, and the vector $\vec{a}$ and the vector $\vec{b}$ are similar. Generalizing this principle to two-dimensional images leads to Eq:

$$NCC(p_{1i},p_{2j}) =\sum_{w=-m}^{m}\sum_{h=-n}^{n}\left(\frac{\left(\begin{array}{l}I_1(x_{1i}+w,y_{1i}+h)-\overline{I_1(x_{1i},y_{1i})})\\ \cdot(I_2(x_{2j}+w,y_{2j}+h)-\overline{I_2(x_{2j},y_{2j})}\end{array}\right)}{(2m+1)\cdot(2n+1)\cdot\sigma(x_{1i},y_{1i})\cdot\sigma(x_{2j},y_{2j})}\right) \tag{14}$$

Among them:

$$\overline{I((x,y))}=\frac{1}{(2m+1)\cdot(2n+1)}\sum_{w=-m}^{m}\sum_{h=-n}^{n}I(x+w,y+h) \tag{15}$$

$$\sigma(x,y)=\sqrt{\frac{\sum_{w=-m}^{m}\sum_{h=-n}^{n}(I(x+w,y+h))^2}{(2m+1)\cdot(2n+1)}-\overline{(I(x,y))}^2} \tag{16}$$

Equation (14) performs similarity computation on the feature point p_{1i} in the reference image and the feature point p_{2j} in the matching image, and $I(x_{1i}+w, y_{1i}+h)$ and $I(x,y)$ represent the pixel values corresponding to the points $(x_{1i}+w, y_{1i}+h)$ and (x,y), respectively, in the image, in order to ensure that the feature point can be used as the center point, the size of the definition window must be odd, so it is written $(2m+1)(2n+1)$ in Eq.

In Equation (15), $\overline{I(x,y)}$ is the gray-scale mean of all pixel points in the gray-scale similarity search window of size $(2m+1)(2n+1)$ in the image.

In Equation (16), $\sigma(x,y)$ is the gray level mean square error of all pixel points in the gray level similarity search window of size $(2m+1)(2n+1)$ in the image.

The NCC sets two sliding correlation windows centered on the feature points (x_{1i}, y_{1i}) and (x_{2j}, y_{2j}) with dimensions of length $2m+1$ and width $2n+1$, and computes their luminance mean and variance, respectively. The similarity quantity value $NCC\left(p_{1i}, p_{2j}\right)$'s takes values between -1 and 1.

III. D. 2) Basic flow of image matching

The main steps in gray scale based image matching are:

First the images to be matched are preprocessed. Then the images to be matched are subjected to certain geometric transformations (translation, rotation, etc.) and the gray scale statistical features of the two images are calculated according to the similarity measure function. The similarity measure of the two images is used as the objective function value, and the matching parameters are used as the variable values (translation distance, rotation angle, etc.). In this way the image matching problem is transformed into a multivariate function to find the global extreme points. Finally, search algorithms such as QGA and optimization strategies are used to search. When the global extreme values are searched, the matching is considered successful.

(1) Image preprocessing

In grayscale-based image matching, image preprocessing mainly includes image noise filtering and correction and image enhancement. In gray-scale image matching, if the quality of the two images to be matched meets the requirements, there is usually no need for preprocessing, but through preprocessing can improve the quality of image matching, more effective search. Preprocessing takes some time and may reduce the matching time.

(2) Geometric transformation of images

The geometric transformation of the image is in accordance with the search space of the image matching image translation, rotation and other operations. Sampling interpolation operation is required in general and in this the bilinear interpolation method is used.

Use $[S]$ to denote the largest integer not exceeding S, then:

$$u=[u_0] \tag{17}$$

$$v=[v_0] \tag{18}$$

$$\alpha=u_0-[u_0] \tag{19}$$

$$\beta=v_0-[v_0] \tag{20}$$

Interpolate $f(u_0,v_0)$ based on (u_0,v_0) 4-neighborhood grayscale values, first make horizontal interpolation.

STEP1: Find $f(u_0,v)$ from $f(u,v)$ and $f(u+1,v)$. As shown in equation (21):

$$f(u_0,v)=f(u,v)+\alpha[f(u+1,v)-f(u,v)] \tag{21}$$

STEP2: Find $f(u_0,v+1)$ from $f(u,v+1)$ and $f(u+1,v+1)$. As shown in equation (22):

$$f(u_0,v+1)=f(u,v+1)+\alpha[f(u+1,v+1)-f(u,v+1)] \tag{22}$$

STEP3: Do vertical interpolation as shown in equation (23):

$$\begin{aligned} f(u_0,v_0) &= f(u_0,v)+\beta[f(u_0,v+1)-f(u_0,v)] \\ &= f(u,v)(1-\alpha)(1-\beta)+f(u+1,v)\alpha(1-\beta) \\ &\quad +f(u,v+1)(1-\alpha)\beta+f(u+1,v+1)\alpha\beta \end{aligned} \tag{23}$$

The essence of the bilinear interpolation method is to do horizontal two-direction, vertical three-time linear interpolation based on the gray value of four neighboring points.

(3) Similarity Measure. Apply normalized interrelationship measure.

(4) Optimization process. In image matching, the optimization process is mainly reflected in the search strategy. It can effectively reduce the search points and improve the purpose of search accuracy and speed.

III. D. 3) Improved Quantum Genetic Algorithm Based Image Matching

The specific flow of image matching based on improved quantum genetic algorithm is shown in Fig. 1.

(1) Define the similarity measure. The normalized correlation measure (NCC) is applied in this chapter.

(2) Select the parameter space and encoding method, the parameter space selects the translation and rotation angles in the X, Y direction, assuming that the size of the base image is (M,N) and the size of the image to be matched is (m,n). Then the size of the search space is $(M-m,N-n)$.

(3) Parameters of the algorithm. The GQGA algorithm and the QGA algorithm are chosen for comparison and to verify the effectiveness of the algorithm.

(4) Initialize the population. The probability amplitudes of chromosomal genes are all $1\sqrt{2}$.

(5) Judge the termination condition, if not satisfied, execute the next step. Otherwise end the matching process.

(6) Calculate the individual fitness value. First observe the quantum chromosome to get the real range of individual variables (pixel positions), and then calculate the fitness value of the individual by similarity measure. It should be added that an interpolation step is required to calculate the similarity measure of two images.

(7) Update the individual and keep the optimal value.

(8) Return to step (5).

(9) Output the matching result. Where steps (5) to (8) are algorithmic steps that can be replaced with the GQGA algorithm and QGA algorithm proposed in this paper.

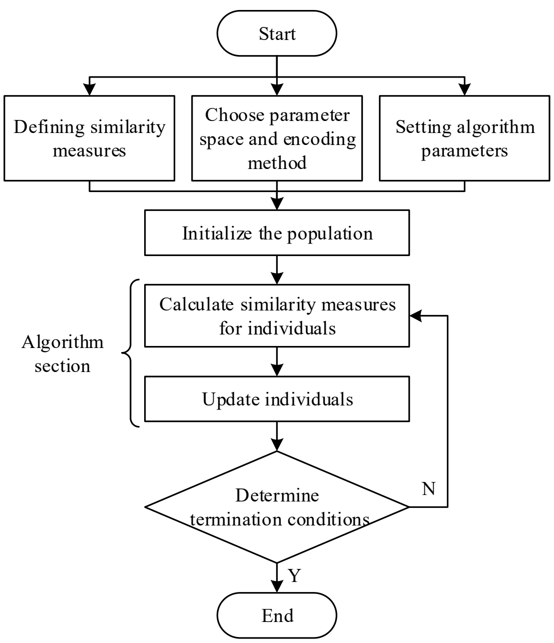

Figure 1: A flowchart of improved quantum genetic algorithm image matching

IV. Analysis and application of sports action image matching techniques

IV. A. Performance analysis of the improved quantum genetic algorithm

In order to test the performance of the improved quantum genetic algorithm, the classical genetic algorithm, the standard quantum genetic algorithm, and the improved quantum genetic algorithm are tested using the Griewank function, the Gramacy&Lee function, the Ackley's function, and the Rastrigin's function.

The operating parameters of the classical genetic algorithm are chosen as follows: population size N=30, crossover probability p_c=0.9, variance probability p_m=0.3, and the maximum number of iterations G=300. The operating parameters of the standard quantum genetic algorithm are chosen as follows: population size N=30, and the angle of rotation for the quantum revolving door size $\Delta\theta = 0.03\pi$. The operating parameters of the improved quantum genetic algorithm are selected as follows: population size N =30, population grouping n =3, maximum number of iterations G =300, and quantum variation determination threshold c =0.5.

The experimental test results of classical genetic algorithm, standard quantum genetic algorithm and improved quantum genetic algorithm for Griewank's function, Gramacy&Lee's function, Ackley's function, and Rastrigin's function were randomly selected, and the number of iterations was plotted against the values of the function as a dotted line graph.

The test results for the Griewank function are shown in Figure 2. The results of one random experiment shown show that the classical genetic algorithm, the standard quantum genetic algorithm, and the improved quantum genetic algorithm find the optimal value at the 87th, 62nd, and 50th iterations, respectively. The optimal value is 0.000. It can be seen that in terms of problem solving speed, the classical genetic algorithm is the slowest, the standard quantum genetic algorithm is in the middle, and the improved quantum genetic algorithm is the fastest.

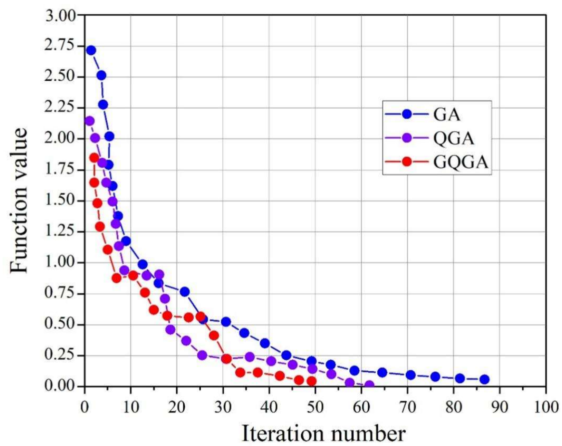

Figure 2: Test results of the Griewank function

The test results for the Gramacy&Lee function are shown in Fig. 3. The three algorithms find the optimal value in the 68th, 56th, and 52nd iterations of the presented randomized one time experimental results, respectively. The optimal values of the three algorithms are -0.712, -0.897, and -0.865, respectively. It can be seen that, as far as the problem solving speed is concerned, the convergence accuracy of the quantum genetic algorithm and the improved quantum genetic algorithm is a little bit higher.

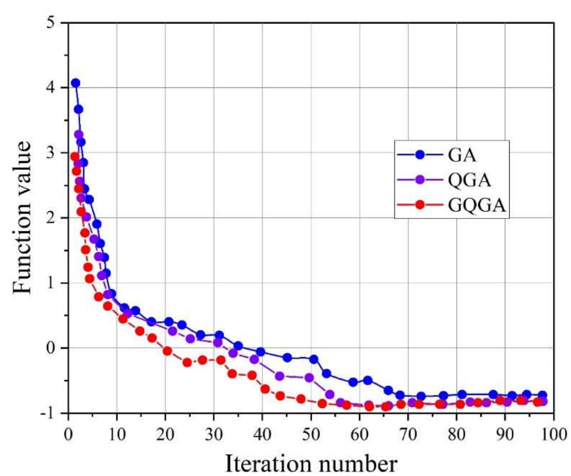

Figure 3: Test results of the Gramacy&Lee function

The test results of Ackley's function are shown in Fig. 4. In the results of one randomized experiment, Algorithm GA, Algorithm QGA, and Algorithm GQGA searched for the optimal value at the 70th, 60th, and 40th times, respectively, and the optimal value of each algorithm was 0.000.

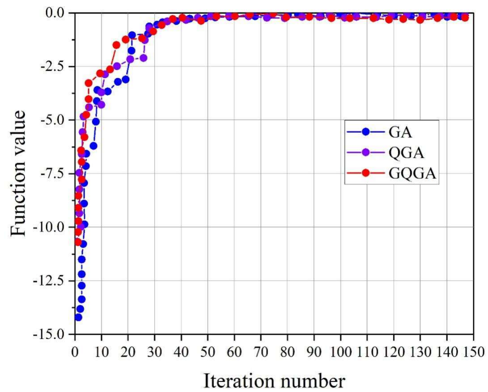

Figure 4: The test results of the Ackley's function

The results of Rastrigin's function test are shown in Fig. 5. Algorithm GA, Algorithm QGA, and Algorithm GQGA find the optimal value by iteration, and the optimal value is 0.000. Algorithm GQGA is faster than Algorithm GA and Algorithm is QGA to find the optimal value by 5 times and 30 times, respectively, and Algorithm GQGA finds the optimal value by only 65 iterations.

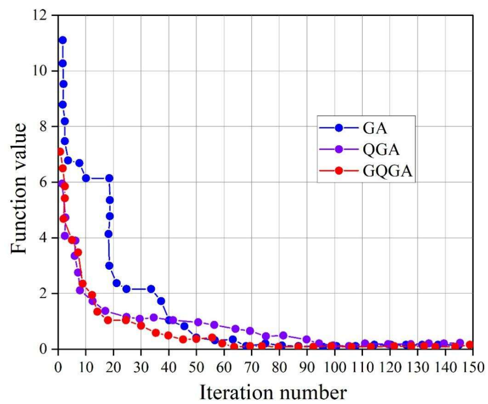

Figure 5: The Rastrigin's function test results

Under the same test conditions, 50 tests are randomly conducted and their mean values are taken for the comparison of experimental data and the comparison results are demonstrated by the following table. Comparison of the experimental results of Algorithm GA, QGA and GQGA is shown in Table 1. It can be seen that 50 experimental simulations are performed randomly under the same experimental conditions.

Table 1: The algorithm is compared with the GQGA experiment

Function	Algorithm	Average optimal solution	Average iteration times
Griewank	GA	0.00005	88.52
	QGA	7.32E-10	63.07
	GQGA	1.19E-09	49.86
Gramacy&Lee	GA	-0.071263	69.15
	QGA	-0.897054	56.37
	GQGA	-0.865997	52.69
Ackley's	GA	-0.012650	71.23
	QGA	6.02E-08	62.04
	GQGA	2.13E-07	43.26
Rastrigin's	GA	-0.00843	95.78
	QGA	0.00015	71.54
	GQGA	0.00003	65.16

In the Griewank function, the average number of iterations of the improved quantum genetic algorithm is improved by 43.67% compared with the classical genetic algorithm. The improved quantum genetic algorithm has a faster convergence rate, requires fewer iterations to reach the optimal value, and the optimal solution of the function obtained maintains the convergence accuracy of the quantum genetic algorithm, which is higher than that of the classical genetic algorithm.

IV. B. Sports action image processing using algorithm GQGA

In this section, experiments are designed to test the segmentation accuracy and time performance of the algorithm GQGA. The principles of the three quantum genetic algorithms that were tested for comparison in the noise immunity and search performance tests are shown in Table 2.

Algorithm QGA1 uses the one-dimensional maximum entropy principle, Algorithm QGA2 uses the method of randomly generating a threshold solution, and Algorithm QGA3 uses a fixed rotation angle.

Table 2: Three algorithms of the experiment

Algorithm	Entropy	Generating threshold strategy	Rotation strategy
QGA1	One-dimensional	half-random	adaptive angle
QGA2	Two-dimensional	random	adaptive angle
QGA3	Two-dimensional	half-random	fixed angle

Experimental hardware environment: processor CORE2 E7500 with 2.93 GHz main frequency, graphics card ATIRADEON HD 4300/4500 Series, software environment: MatlabR2021a.

Segmentation of sports action images (ball sports, track and field sports, gymnastics actions, martial arts actions) using QGA1, QGA2, QGA3 and QGA4 respectively is used to test the performance of the GQGA method proposed in this paper in optimizing the performance of the algorithm.

The parameters of each algorithm are set as follows: gen=500, population=20, μ =0.0001, where the fixed rotation angle θ =0.006 π is used in QGA3.

Each algorithm runs 200 segmentation operations independently, and the average maximum entropy (me), average number of generations (mg), and average time (mt, in s) data statistics after segmentation when C = 1, 2, 3, and 4 are shown in the figure below.

The average maximum entropy statistics of the four algorithms are shown in Fig. 6. It should be noted that the average maximum entropy value of algorithm QGA1 is only 0.1 in gymnastics action images when C =1. Algorithm GQGA maintains a larger average maximum entropy value at C =1, 2, 3, and 4 to accurately segment all types of sports action images.

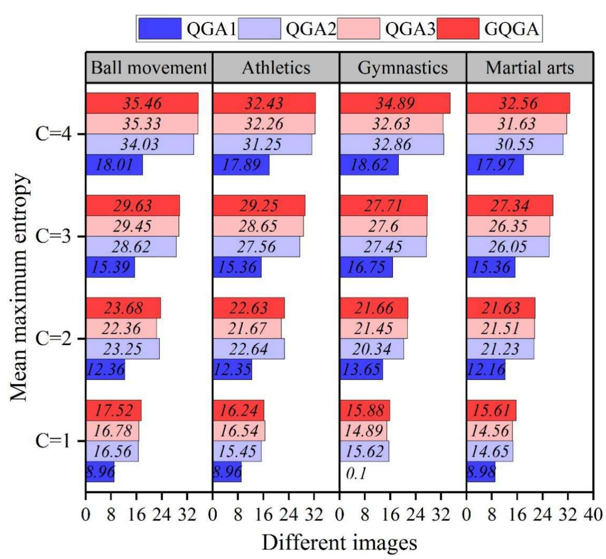

Figure 6: The average maximum entropy of four algorithms

The average generation value statistics of the algorithm are shown in Figure 7.

When C = 1, the average surrogate value of Algorithm QGA1 does not exceed 20 in any of the four categories of sports action images.

From the figure, it can be seen that some of the average generation values of Algorithm QGA2 are similar to those of Algorithm GQGA.

When C takes the value of 4, the average generation value of Algorithm QGA2 in martial arts action images is 231, which is higher than that of Algorithm GQGA, and the average generation value of Algorithm QGA3 is the largest, which is 312.

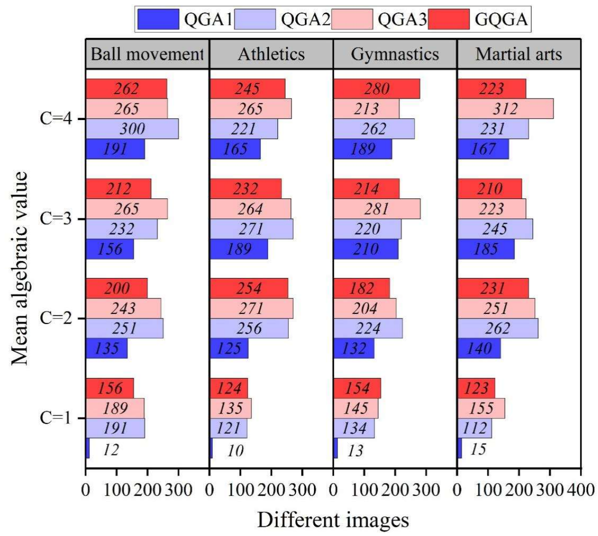

Figure 7: The average algebraic value of the algorithm is calculated

The average time statistics of each algorithm are shown in Fig. 8. The figure shows that the average time consumed by Algorithm QGA1 for the four types of sports action images when C takes the values of 1, 2, 3, and 4 is less than 1 s. While Algorithm QGA3 is compared with Algorithm GQGA, Algorithm GQGA has fewer iterations in general, and the algorithm is faster because the algorithm in this paper adopts the adaptive rotation strategy, which accelerates the convergence speed. Combining the average maximum entropy, average number of generations, and average time of the four algorithms, it can be seen that Algorithm GQGA has comprehensive advantages and can be applied to sports action image processing.

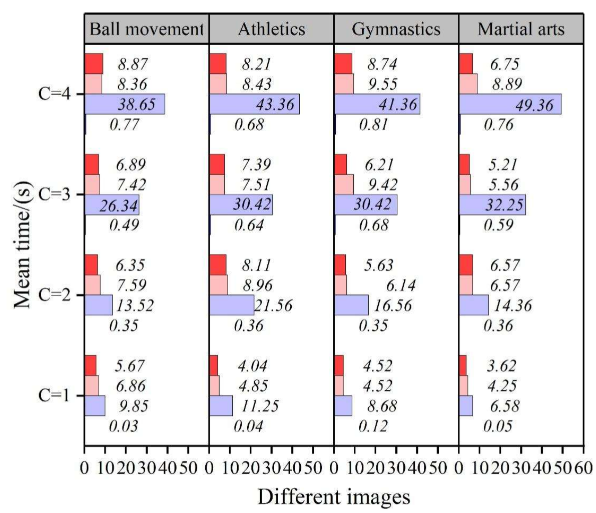

Figure 8: Average time statistics for each algorithm

IV. C. Effectiveness of Professional Development for Physical Education Teachers

The image matching technology based on improved quantum genetic algorithm is applied to sports action image processing, which is beneficial to improve the professional action technology of physical education teachers, and to facilitate the teaching of more professional actions by physical education teachers. This paper focuses on analyzing the effect of professional development and teaching ability improvement of physical education teachers.

Experimental subjects: this paper takes the teaching ability improvement strategy of physical education intern teachers as the research object, in which the survey sample of physical education intern teachers takes the students of physical education majors of grade 2023 in the colleges and universities admitting sports majors in high school in undergraduate batch in Anhui Province as the survey object.

The undergraduate colleges in Anhui Province that admitted high school physical education students in 2019 are Anhui Normal University, Anqing Normal University, Huaibei Normal University, Fuyang Normal University, Huainan Normal College, Chaohu College, Chuzhou College, Huangshan College, Suzhou College, Wanxi College, and Bozhou College, totaling 10 undergraduate colleges and universities.

The initial stage of the internship was expected to distribute 880 questionnaires, and finally 837 valid questionnaires were collected, with an effective recovery rate of about 95%. After the collection was completed, the collected questionnaire data were analyzed for reliability and validity using data analysis software.

In this part, the overall level of teaching ability of physical education trainee teachers at the initial stage of internship in Anhui Province was investigated and counted, and the results of the survey on the overall situation of teaching ability at the initial stage of internship are shown in Table 3. The overall mean score of teaching ability is 3.49, which is at the average to good level. The mean value of the ability to identify and analyze problems in the classroom was 3.66, indicating that the physical education intern teachers had good problem identification ability. There are still some deficiencies in personal teaching preparation, assimilation of others' teaching experience, and classroom information collection.

Table 3: The results of the general situation of the initial stage of the internship

Dimension	Term number	Sample size (N)	Mean (M)	Standard deviation (SD)
Ability to prepare for personal teaching	5	837	3.25	0.523
The ability of other people to learn from the experience	5	837	3.37	0.634
Classroom collection information ability	7	837	3.43	0.787
Classroom discovery and analytical ability	6	837	3.66	0.766
Classroom action adjustment ability	6	837	3.45	0.823
Class evaluation ability	7	837	3.68	0.898
After-school teaching results reflect the ability	3	837	3.59	0.594
Total average	3.49			

The results of the survey on the overall level of teaching competence at the end of internship stage are shown in Table 4. This part investigates and counts the overall level of teaching ability of sports intern teachers at the end stage of internship in Anhui Province. The sports movement image matching technology based on the improved quantum genetic algorithm was used in the internship stage to improve the specialization of sports movements.

From the total average score of teaching ability, it can be seen that the teaching ability of sports internship teachers at the end of the internship was improved by 0.96 points, and the total average score was 4.45, which was at the level of good to excellent, which prompted the professional level and teaching ability of sports internship teachers to be recognized.

The sports movement special enhancement strategy facilitates the sports intern teachers to better prepare for teaching, absorb the sports movement related teaching experience, and be able to find out the problems of students' movement from whether the sports movement image matches or not, and provide targeted guidance.

Table 4: The overall situation of the teaching ability of the end of the internship

Dimension	Term number	Sample size (N)	Mean (M)	Standard deviation (SD)
Ability to prepare for personal teaching	5	837	4.53	0.824
The ability of other people to learn from the experience	5	837	4.26	0.715
Classroom collection information ability	7	837	4.41	0.863
Classroom discovery and analytical ability	6	837	4.29	0.747
Classroom action adjustment ability	6	837	4.47	0.845
Class evaluation ability	7	837	4.52	0.798
After-school teaching results reflect the ability	3	837	4.64	0.823
Total average	4.45			

The changes in the professional development and teaching competence of the PE trainee teachers between the initial and the end stages of the internship are shown in Table 5. The physical education movement aspect included both standard movement demonstration and error movement diagnosis. The teaching academic ability includes teaching sports specialized text knowledge, teaching movement knowledge, understanding students' movement cognitive level, adjusting teaching according to students' movement level, and teaching targeted sports movement training.

By applying the sports action image alignment technology based on improved quantum genetic algorithm to sports action specialization, it can be found that both in terms of sports action and academic teaching ability, the professional level and teaching ability of physical education trainee teachers have been effectively improved. Therefore, from the quantum genetic algorithm to optimize the sports action image alignment technology, the sports action for the refinement of mastery, for the mastery of professional knowledge of physical education teachers as well as classroom teaching is helpful, and can extend the feasible path of the professional development of physical education teachers and the improvement of teaching ability.

Table 5: The professional ability of sports intern teachers changes

Dimension		Sample size (N)	The mean of the initial phase of the internship (M)	The mean of the end of the internship (M)
Sports technique	Standard action demonstration	837	3.25	4.12
	Error diagnosis	837	3.35	4.23
Academic ability	Text knowledge teaching	837	3.42	4.04
	Action knowledge teaching	837	3.52	4.39
	Understand the level of student behavior	837	3.64	4.15
	Adjust the teaching according to the students' action level	837	3.26	4.08
	Training and training of targeted sports	837	3.38	4.26
Total mean			3.40	4.18

V. Conclusion

This paper optimizes the matching performance of the algorithm on sports action images by improving the quantum genetic algorithm, and applies the method to the professional teaching development of physical education teachers in an attempt to achieve the purpose of enhancing the professional development and teaching ability of physical education teachers.

(1) Addition of adaptive computation method to algorithm GQGA has advantages in terms of number of iterations and convergence accuracy.Algorithm GQGA seeks the optimal value of 0.000 at the 50th iteration under the Griewank function test. Under the four categories of sports classic action image matching test, the combined me, mg, and mt values of each algorithm, algorithm GQGA has a smaller average processing time than algorithm QGA3 while maintaining the maximum me value. The reason may be because this paper adds the corner mechanism of quantum revolving door in the algorithm GQGA, which accelerates the convergence speed.

(2) The sports action image matching technology based on the improved quantum genetic algorithm is applied to the professional development of physical education trainee teachers, and it can be seen from the comparison of the total average scores of teaching ability in the initial stage of the internship and the end stage of the internship that the improvement of the sports action technology can effectively influence the professional development and teaching ability of physical education teachers.

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