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A Multidimensional Adaptive Entropy Cloud-Model-Based Evaluation Method for Grid-Related Actions

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Abstract: Smart grid training system needs to evaluate actions during power grid operations in order to complete training for relevant personnel. The commonly used action evaluation methods are difficult for evaluating fine actions during power grid operations, and the evaluation results are subjective. The use of an effective method to evaluate the actions of the power grid operation is important for improving the smart grid training system, enhancing the skills of the trainers, and ensuring the personal safety of operators. This paper proposes a cloud attention mechanism and an evaluation method of grid-related actions based on a multidimensional adaptive entropy cloud model to complete the evaluation of fine actions in the grid's operation process. Firstly, the OpenCV technique is used to obtain the data related to hand actions during grid operation and to extract the action features to complete the construction of multiscale date sets; then, the adaptive entropy weight matrix at different scales is constructed based on multiscale data sets using the cloud attention mechanism, and the basic cloud model is generated from original hand-action feature data; finally, the multidimensional adaptive entropy cloud model is constructed by the adaptive entropy weight matrix and the basic cloud model, and the multidimensional adaptive entropy cloud model obtained is compared with the multidimensional adaptive entropy cloud model generated based on the standard action features in the same space to obtain the evaluation level of the hand action. The results show that the evaluation method of grid-related actions based on the multidimensional adaptive entropy cloud model can solve the mutual mapping problem between quantitative indicators and qualitative evaluation results in the evaluation of grid operation processes relatively well, and it effectively solves the subjectivity of the weight assignment of evaluation indicators, which can be used for the evaluation of fine actions in the grid's operation processes.

Keywords: power grid training; cloud model; cloud attention mechanism; action evaluation

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1. Introduction

A power grid system is responsible for important economic operations and plays an important role in ensuring sustainable economic development. The safety of the electricity grid system has always been a top priority. However, traditional grid training is inflexible, costly, and can threaten the lives of trainers. Therefore, training in virtual environments will be a trend in the future, and modern medical fields are already teaching procedures such as deconstruction in virtual environments [1]. The implementation of VR technologies for grid training can be the most effective complement and enhancement relative to traditional training.

A prerequisite for evaluating grid-related actions is the ability to capture subtle changes in hands. By using VR technology and OpenCV, relevant hand movement data can be accurately obtained. By using VR technology, the degree of hand tremors can be accurately obtained for the treatment of Parkinson's disease [2], and by using OpenCV technology, the 3D coordinates of objects can be obtained from images and their 3D models can be reconstructed [3]. In this paper, VR technology is combined with the theory of cloud modeling. Via OpenCV, the coordinates, angular velocity, and motion direction of the wrist and fingers can be obtained, and the acquired data can be characterized and the key data can be extracted to construct the data set required for the experiment. Moreover, combining the theory of the cloud model can be performed to complete the evaluation of grid-related actions.

There are many fine operations in the process of grid operation, and some small errors may cause serious consequences. The traditional action methods tend to ignore some inconspicuous errors, and the evaluation results are subjective. Therefore, the evaluation of grid operations is an extremely important part of the smart grid training system. Questions with respect to how to evaluate minor errors in grid-related actions and how to objectively evaluate grid-related actions are of great significance for supplementing and developing the smart grid training system.

The main contributions of this paper are as follows. 1. Using OpenCV is proposed to obtain the motion data of the hand in the process of grid operation and to complete the automatic classification of the data based on the artificial intelligence algorithm to construct multiscale data sets. 2. The concept of a cloud attention mechanism is proposed to obtain the evaluation index weights of action features at different scales, namely the adaptive entropy weight matrix, which can optimize the cloud model generated based on action features so that the cloud model can reflect the features of the same action at different scales. 3. An evaluation method of grid-related actions based on a multidimensional adaptive entropy cloud model is proposed to overcome the shortcomings of traditional motion-evaluation methods and to improve efficiency and effectiveness when evaluating grid-related actions.

The organizational structure of this article is as follows: 1. Introduction: This paper introduces the application of VR technology in a smart grid training system and puts forward a method for improving the efficiency and accuracy of action evaluation in the process of grid operation. Finally, the contribution and organizational structure of this paper are introduced. 2. Reference: This paper introduces current research results in the field of action evaluation and cloud model in the world, summarizes unsolved problems, and puts forward the solution of this paper. 3. Action evaluation method: This paper introduces the method of constructing multiscale data sets and introduces the cloud attention mechanism and cloud model while completing the construction of a multidimensional adaptive entropy cloud model based on an adaptive entropy weight matrix and basic cloud model. 4. Application instances: The method of obtaining hand action data using OpenCV technology is introduced, and the experimental results are analyzed. 5. Conclusions. To summarize the entire paper, it is concluded that the grid-related action evaluation method based on multidimensional adaptive entropy cloud model can be applied to the evaluation of fine hand actions in virtual environments. It is proved that the multidimensional adaptive entropy cloud model based on an adaptive entropy weight matrix and basic cloud model can improve the efficiency and effectiveness of action evaluations in the process of grid operations.

2. Reference

Human action evaluation has become an important area in computer vision applications, and there have been many studies conducted to automatically evaluate the quality of human actions by designing computational models and evaluation methods [4]. Action evaluation has been widely used in the medical field. In [5], an action evaluation framework is proposed to assess the degree of correlation between people's posture and health and to identify postures that may contribute to musculoskeletal disorders. There are also some applications in rehabilitation medicine, where patients need an assessment of the movement action specification of the movements they perform when they perform rehabilitation exercises at home. In [6,7], a deep-learning-based framework is proposed to assess rehabilitation exercises in order to evaluate the quality of people's movements at home.

In [8], a framework for objective skill assessments based on motion trajectory data was proposed by using three classification methods, k-nearest neighbor, logistic regression, and support vector machine, to automatically assess the performance of surgeons at different levels of expertise. Action evaluation is similarly applied to action scoring for competitions, and an ED-TCN-based p3D fusion network S3D was proposed by [9], which significantly improves the performance of the UNLV-Dive data set, which is the first algorithm that progressively scored sports actions. In [10], a multi-task learning method was proposed, and the correlation between the scores obtained from the C3D-AVG-MTL model judgments and the true judgment scores reached 90.44%. In [11], a shared model across multiple action samples is proposed to benefit from knowledge sharing, which allows for better evaluations of actions.

Cloud models, as an important cognitive computing model, have been applied to many areas of artificial intelligence to accomplish the transformation from quantitative data to qualitative concepts [12]. In [13], a method for the operational safety assessment of cross-seat monorail vehicle systems based on a cloud model and an improved evaluation method was proposed. In [14], a bacterial foraging optimization algorithm based on a normal cloud model was proposed for obtaining a positive kinematic solution. In [15], a fuzzy and contradictory data fusion method for multi-sensor data based on cloud models and the improved evidence theory was proposed, and the feasibility of the method demonstrated that it could provide some reference value for multi-sensor information fusion. In [16], the concept of time series cloud and the generation algorithm were proposed for detecting the uncertainty of data changes. In [17], a risky large-group decision-making method based on FCM clustering and the cloud model was proposed to investigate the psycho-behavioral characteristics of decision makers' avoidance. In [18], an evaluation method based on a combination of a finite interval cloud model and genetic algorithm weighting was proposed to evaluate the suitability of urban underground space. Based on the cloud model and qualitative flexible multi-criteria approach, an integrated multi-criteria decision model was proposed in [19] to evaluate the green performance of firms under economic and environmental criteria. In [20], a cloud-model-based trust evaluation method for clustered wireless sensor networks was proposed, and it achieved the qualitative and quantitative conversion of sensor node trust metrics for better trust assessments. Based on the cloud model theory and hierarchical techniques, a novel integrated model for failure modes and impact analyses was proposed in [21] to evaluate and rank the risk of failure modes. In [22], an evaluation of the safety of urban rail transit operations using a cloud model and an improved standard importance method was proposed. There are few studies that have been conducted to improve the cloud model, and there is no corresponding published literature on the application of cloud models to action evaluation.

The attention mechanism is widely used in the field of action recognition, which improves the expression of action features and recognition accuracies [23]. In [24], an attention mechanism based on bidirectional long short-term memory is proposed to improve the accuracy of human action recognition in videos. In [25], an adaptive graph transformation network based on kernel attention mechanisms was proposed to improve the accuracy of skeleton-based human action recognition. In [26], a method combining attention mechanisms, convolutional neural networks, and long-term neural networks was proposed to improve the recognition accuracy of continuous massage images with time series. In [27], a new autoregressive model combining a self-attention module and the recursive method is proposed, which improves the authenticity and diversity of point cloud generation. In this paper, the attention mechanism is applied to the cloud model to weight the key cloud drops in the cloud model, which enables the cloud model to have a higher accuracy representation of relevant action features.

There are fewer evaluation methods on grid-related actions and more on the stability of smart grids. Ref. [28] proposed a multi-agent reinforcement learning algorithm for efficient demand responses in smart grids in order to reduce the cost of improving the demand response's performance in smart grids by evaluating the overall system performance of current smart grids. Ref. [29] used fuzzy multi-criteria decision making to evaluate the reliability of smart grids from the user's perspective, analyzing and prioritizing three criteria, "Big Data Management", "Communication System", and "System Functionality", based on triangular fuzzy numbers and triangular membership functions. In [30], STGCN was proposed to implement the recognition of grid-related hand actions and to match them with standard actions to complete the action evaluation, which improves the correct rate of hand action recognition; the method can only judge the correctness of the action, but it is unable to evaluate the accuracy of the action.

In summary, the power industry needs an action evaluation method to improve smart grid training systems. This paper proposes an evaluation method for grid-related actions based on a multidimensional adaptive entropy cloud model. Firstly, the quantitative value of hand motion data is converted into a qualitative concept to evaluate whether the motion change conforms to the motion characteristics of the job by using the cloud model; then, the cloud attention mechanism is used to optimize the cloud model to construct multidimensional adaptive entropy cloud models and to enlarge subtle differences of similar actions in order to make the results of action evaluation more effective and objective.

3. Action Evaluation Method

Human action evaluation has become a popular research problem in recent years. The evaluation of actions has a strong pertinence in professional fields. It must be combined with expert experience in the field to construct a professional evaluation standard. It not only needs to compare the appearance similarity of the action but also needs to evaluate the standardization, quality, and even artistry of the action so as to assist people in the depth analysis of actions. Therefore, traditional action evaluation often depends on people's subjective consciousness. These methods ignore the high-level features contained in many hand actions, which makes the results of action evaluations lack effectiveness. Fine hand actions contain important operational information and subtle differences. The evaluation of hand action in power grid operation training needs to be more objective and reliable.

This paper proposes a grid-related action evaluation method based on a multidimensional adaptive entropy cloud model to solve some problems existing in traditional action evaluations and to improve the effectiveness of action evaluations. The cloud model can convert the numerical results of OpenCV's acquisition of hand motion data into a qualitative concept to evaluate whether the motion's changes conform to the motion characteristics of the job. The cloud attention mechanism can objectively obtain the weight of the evaluation index for different scales of data, that is, the adaptive entropy weight matrix of different scales. Combined with the cloud attention mechanism, the cloud model can show the characteristics of the same action at different scales. Finally, the multidimensional adaptive entropy cloud model of the test action and standard action is compared to obtain the evaluation level of the hand's action, and the evaluation of the tester's action is completed.

3.1. Method Process Design

In this paper, a multiscale data set is constructed by using the data obtained by OpenCV, and the evaluation of fine hand action is completed based on the multidimensional adaptive entropy cloud model for assisting power grid operators in correcting irregular operations during their own training. This is performed via cooperation with industry-related professional staff using UE4 and installing OpenCV plugins, and OpenCV technology is used to collect their professional hand operation actions. Considering readability, action data are recorded in JSON format to record the key points of the hand skeleton and are preprocessed based on the KNN. Multiscale data sets are constructed by multiscale division with the wrist's motion distance as the boundary. The differences of fine action at different scales are also different. Therefore, the cloud attention mechanism is used to obtain the corresponding adaptive entropy weight matrix by analyzing the data sets of different scales. Based on the original hand action feature data, the cloud droplets that can construct the basic cloud model are generated. Each cloud droplet is multiplied by the corresponding weight in the adaptive entropy weight matrix, and the new cloud droplets can form a multidimensional adaptive entropy cloud model. Finally, the obtained multidimensional adaptive entropy cloud model and the multidimensional adaptive entropy cloud model based on standard action feature generation are compared in the same space to complete the evaluation of fine hand actions and to improve the final action evaluation module in the smart grid training system. The detailed flow chart for evaluating fine hand movements are shown in Figure 1.

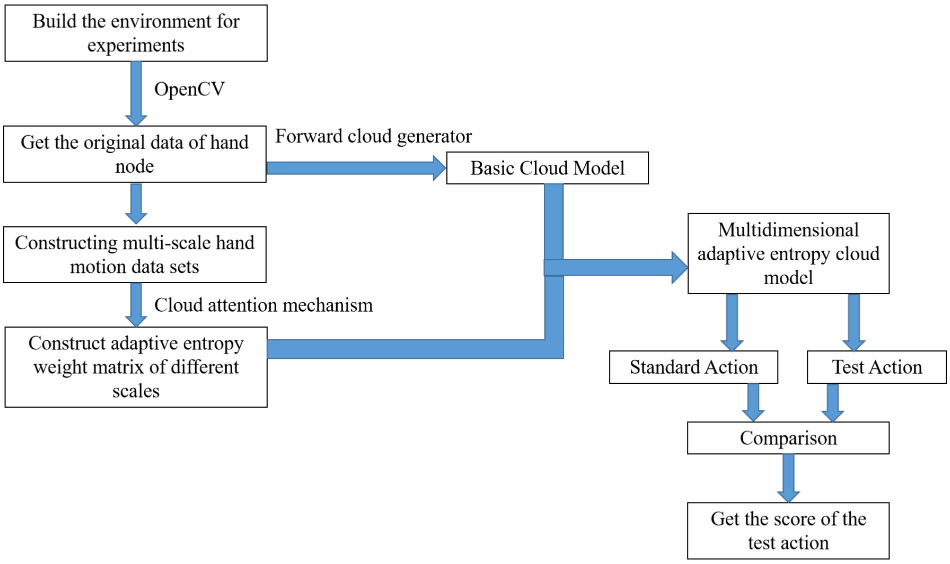

Figure 1. Detailed flow chart of action evaluation.

3.2. Cloud Model

The concept of a cloud model is proposed on the basis of probability distributions and membership functions. It describes the randomness, fuzziness, and their relationship in the objective world using the uncertainty transformation between qualitative concepts and quantitative values. In the objective world, there are generally qualitative concepts and quantitative data with objective correlations. Just as the action evaluation mentioned in this paper, it is necessary to convert the quantitative data of fine hand action with the qualitative concept of evaluating whether the action's change conforms to the action characteristics of the operation so that the action evaluation is supported by data.

Let U be a quantitative domain represented by exact numbers, and C be a qualitative concept on U. If the quantitative value $x \in U$, x is a random realization of the qualitative concept C, and the affiliation $\mu(x) \in [0, 1]$ of x to C is a random number with a stable tendency, as shown in Formula (1), the distribution of x on the quantitative domain U is called a cloud, each x is called a cloud droplet, and the cloud model comprises several cloud droplets.

$$\mu : U \to [0,1] \qquad \forall x \in U \qquad x \to \mu(x). \tag{1}$$

The relationship between the qualitative concept and the quantitative quantity, on domain U, is not a one-to-one but a one-to-many mapping relationship. The degree of the affiliation of x to C is a probability distribution and not a definite one, thus forming an affiliation curve range composed of many cloud droplets. As shown in Figure 2, each cloud droplet is a quantitative representation of the qualitative concept via conversion. A single cloud droplet does not have much influence, but the shape of the entire cloud can reflect the characteristics of the qualitative concept.

The normal cloud model is the main type of cloud model. The normal cloud model uses a set of independent parameters to express a qualitative conceptual digital feature to reflect conceptual uncertainty. This set of parameters is represented by three numerical eigenvalues: expectation Ex, entropy En, and hyper entropy He. Expectation (Ex) is the most representative point of this qualitative concept in the domain space, which is the most typical sample point of this concept's quantification. Entropy (En) represents the measurable granularity of a qualitative concept. The larger the entropy, the more macroscopic the concept. It also reflects the uncertainty of the qualitative concept; in the domain space, the quantitative concept can accept the size of the range of values, namely ambiguity. Hyperentropy (*He*) is a measure to describe the uncertainty of entropy, which represents the randomness of the sample of the qualitative concept value, and it is used to reveal the relationship between fuzziness and randomness.

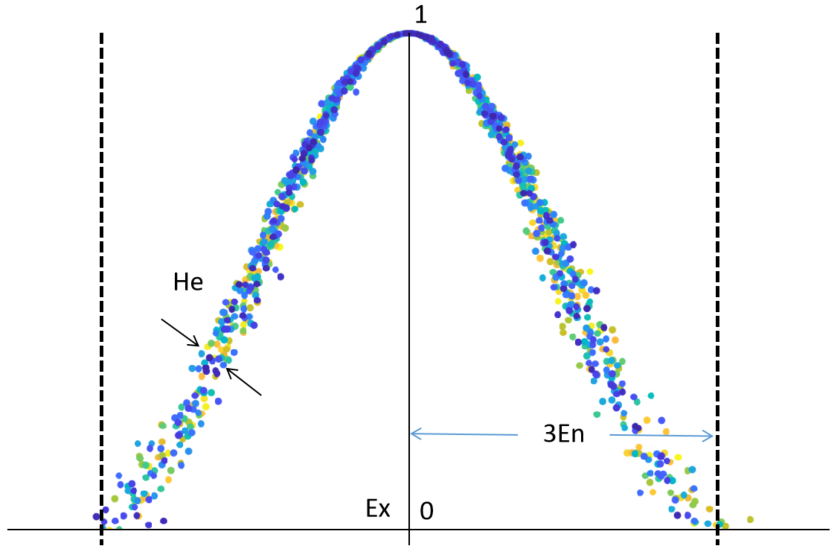

Figure 2. Cloud model diagram.

The cloud model can be generally divided into a forward cloud and reverse cloud according to different mechanisms and mapping directions. In order to realize the mutual conversion from a qualitative concept to a quantitative value, it is often necessary to use a cloud generator (CG). A cloud generator includes a forward cloud generator, reverse cloud generator, and conditional cloud generator. This paper needs to use the forward cloud generator to convert the quantitative data of hand motion to the qualitative concept of evaluating whether the motion's change conforms to the motion characteristics of the operation. A diagram of the forward cloud generator is shown in Figure 3.

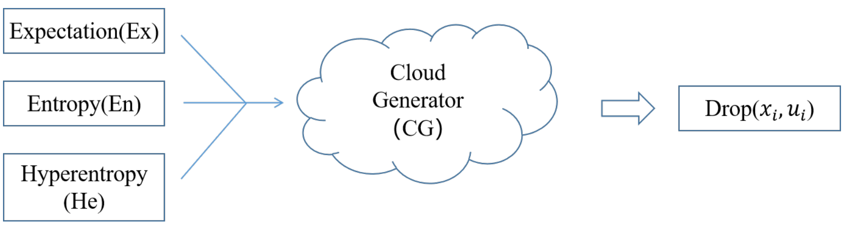

Figure 3. Forward cloud generator.

The basic function of the forward cloud generator is to generate cloud droplets based on numerical features. The numerical eigenvalues (Ex, En, and He) of a given cloud, the number of cloud droplets n, and the algorithm steps include the following.

(1) Normal random number $En' \sim N(En, He^2)$ is genearted with En as the expectation and He as the standard deviation.

(2) Normal random number $x \sim N(Ex, En'^2)$ is generated with Ex as the expectation and En' as the standard deviation.

(3) Sffiliation degree score μ is calculated by using Formula (2):

$$\mu = e - (x - E_x)^2 / d * E_{n'}^2, \tag{2}$$

where d denotes the number of dimensions; in this paper, the action change features of the hand joint node coordinates in the two-dimensional plane are extracted as inputs of the cloud model, so d is equal to 2.

(4) Let x, μ be called a cloud droplet.

(5) Setps 1 to 4 are repeated until n cloud drops are generated.

It can be seen from the above steps that there are two normal random numbers generated in the forward cloud generation process. Random number En' is affected by hyperentropy, which expresses the randomness and fuzziness of the affiliation. Then, x is randomly generated with random number En as the standard deviation, which indicates that x is a random realization of the quantitative concept. Two random generations constitute a nested relationship and together they determine the distribution of cloud droplets.

3.3. Cloud Attention Mechanism

An attention mechanism is a resource allocation scheme for allocating computing resources to more important tasks and solves the problem of information overload in the case of limited computing power. For example, in the process of human action recognition, the motion information of hands and legs may be more effective than the motion information of the neck and head, so different weights can be assigned to different torsos to improve the efficiency of action recognition processes.

This paper proposes a cloud attention mechanism, which weights some key cloud droplets in the cloud model so that the cloud model can better reflect the motion characteristics with subtle differences. The scale of motion data is different, and the concerned hand joint nodes are also different. When the wrist movement distance difference of an operation in the power operation is small, more attention should be paid to the joint node data on the finger; when the wrist motion distance of an operation in electric operation is quite different, more attention should be paid to the joint node data on the palm and wrist.

The formula for generating the basic cloud model by extracting the numerical features of the cloud from the action features is as follows:

$$f_{cloud} = \sum_{1}^{n} f(E_x, E_n, H_e), \tag{3}$$

where n denotes the number of generated cloud drops.

The cloud attention mechanism determines the weight via the judgment matrix composed of evaluation indicators, which can avoid the subjectivity and uncertainty caused by expert empowerment. Its calculation steps are as follows:

(1) Construct the judgment matrix: Suppose that there are m evaluation objects and n evaluation indexes. r_{ij} represents the value of j $(j = 1, 2, \cdots, n)$ evaluation indexes of the ith $(i = 1, 2, \cdots, m)$ evaluation objects, and the normalized matrix $(r_{ij})_{m\times n}$ is established.

(2) Standardization of indicators: Due to the different units of the selected evaluation indicators, dimensionless processing is needed. This paper uses positive and negative indicators of the range method to quantify it between 0 and 1. The positive index indicates that the index value is positively related to the evaluation's result; negative indicators are the opposite. The calculation formula is as follows:

Positive index calculation formula:

$$f_{ij} = \frac{x_i - min(x_1, x_2, \cdots, x_n)}{max(x_1, x_2, \cdots, x_n) - min(x_1, x_2, \cdots, x_n)}. \tag{4}$$

Negative index calculation formula:

$$f_{ij} = \frac{min(x_1, x_2, \cdots, x_n) - x_i}{max(x_1, x_2, \cdots, x_n) - min(x_1, x_2, \cdots, x_n)}. \tag{5}$$

where f_{ij} represents the standardized result of the value of the jth evaluation index of the ith evaluation object, x_j is the original data value, x_{max} represents the maximum value of the jth evaluation index, and x_{min} represents the minimum value.

(3) The entropy of each indicator is then calculated. Let the entropy value of the index j be H_j, and the calculation method of H_j is as follows:

$$H_j = -\frac{1}{\ln T}\sum_{i=1}^{T} q_{ij}\ln q_{ij}, \tag{6}$$

where $q_{ij} = (1 + r_{ij}) / \sum_{i=1}^{T}(1 + r_{ij})$ denotes the weight of each indicator, and T denotes the evaluation object.

(4) The weight of the jth evaluation index is calculated:

$$W_j = (1 - H_j) / \sum_{j=1}^{n}(1 - H_j), \tag{7}$$

where n denotes the number of evaluation indicators, and W_j is the weight of each evaluation indicator. The n weight values are thus calculated together from the adaptive entropy weight matrix $W_{1\times n} = w_1, w_2, \cdots, w_n$. After adding the cloud attention mechanism, the formula for generating a multidimensional adaptive entropy cloud model can be expressed as follows:

$$f_{cloud} = W_{1\times n} \times \sum_{1}^{n} f(E_x, E_n, H_e). \tag{8}$$

3.4. Construction of Multiscale Hand Action Data Matrix

It is difficult to evaluate the fine action in electrical operations from only one scale. It is necessary to construct a multiscale hand action matrix to analyze the characteristics of actions at different scales. Firstly, the hand timing information in the virtual environment is read by OpenCV technology, as shown in Figure 4.

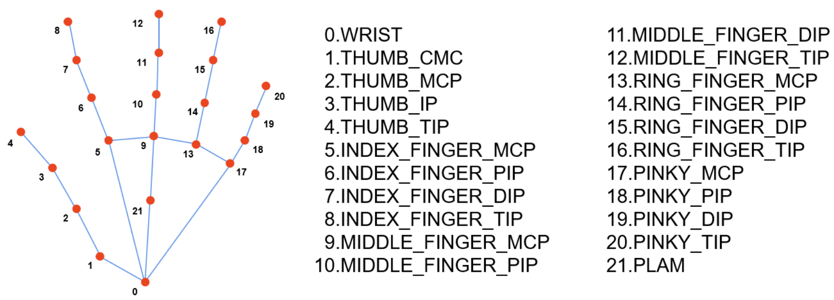

Figure 4. Diagram of hand joint nodes.

In order to analyze the law of gesture motion, it is necessary to construct a multiscale hand action matrix based on the timing information of hand joint nodes extracted by OpenCV technology. The 21st point represents the node of the palm, which is obtained by calculating the center distance of node 9 and node 0. Building a multiscale hand action matrix can be divided into three steps.

(1) The fingertip speed and inter-finger distance L of hand movements in each frame sequence are calculated, and they are defined as follows:

$$L = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \quad (i, j \in [4, 8, 12, 16, 20], i \neq j), \tag{9}$$

$$s_i = \sqrt{(x_{it2} - x_{it1})^2 + (y_{it2} - y_{it1})^2 + (z_{it2} - z_{it1})^2} / t, \tag{10}$$

where s_i is the velocity of fingertip n at this moment; x_{it1}, y_{it1}, and z_{it1} denote the position of fingertip i at the previous moment; x_{it2}, y_{it2}, and z_{it2} denote the position of fingertip n at this moment.

(2) The fixed threshold method is used to analyze the sum of the hand signal's energy and to determine the initial point of the action. If it is less than threshold v, the action is not performed; if it is greater than threshold v, the action performed is defined as a valid action. The hand signal energy E and the sum of hand signal energy are defined as follows:

$$E = (s_1 + s_2 + s_3 + s_4 + s_5), \tag{11}$$

$$E_{sum} = E_{t1} + E_{t2} + \cdots + E_{tn}, \tag{12}$$

where n is taken as 10 by default, indicating that the hand action is analyzed for 10 frames.

(3) Starting from the action's starting point, feature information such as fingertip speed, finger distance, palm position, and wrist position is sequentially filled into the multiscale hand action matrix, as shown in Figure 5.

$$t \downarrow \quad \begin{array}{l} S_{11}S_{12}S_{13}S_{14}S_{15}L_{11}L_{12}L_{13}L_{14}P_{1x}P_{1y}P_{1z}W_{1x}W_{1y}W_{1z} \\ S_{21}S_{22}S_{23}S_{24}S_{25}L_{21}L_{22}L_{23}L_{24}P_{2x}P_{2y}P_{2z}W_{2x}W_{2y}W_{2z} \\ \cdot \\ \cdot \\ \cdot \\ S_{t1}S_{t2}S_{t3}S_{t4}S_{t5}L_{t1}L_{t2}L_{t3}L_{t4}P_{tx}P_{ty}P_{tz}W_{tx}W_{ty}W_{tz} \end{array}$$

Figure 5. Multiscale hand action matrix.

In order to analyze effective actions with different durations, the multiscale hand action matrix of effective actions is processed by frame extraction. In this paper, 20 frames are extracted by dynamic spacing for all actions, and the maximum interval between frames is 1 frame.

In order to obtain the scale information of the actual action, the adaptive entropy weight matrix required to construct the multidimensional adaptive entropy cloud model is determined. After constructing the multiscale hand action matrix, the KNN algorithm is used to divide the action. By calculating the similarity between the sample to be classified and the k categories y_j (j = 1, 2, ..., k), the sample to be classified is divided into a certain category y_j to determine the category of the action. Euclidean distances are usually used to calculate the similarity between the classification sample and each category. Distance L_K is defined as follows

$$L_K = (\sum_{l=1}^{n} |x^l - y_j^l|^p), \tag{13}$$

where n denotes the number of features of the sample; x^l denotes the lth feature of the sample to be classified; y_j^l denotes the lth feature of the jth sample with the known label.

3.5. Action Evaluation Method Based on Multidimensional Adaptive Entropy Cloud Models

In the process of the system evaluation of the entire action, the cloud model should consider the randomness and fuzziness of the action. The grid-related actions evaluation method based on the multidimensional adaptive entropy cloud model uses the cloud attention mechanism to obtain the weight of action features at different scales, which can reduce human influences. Therefore, it is more objective and reliable than the traditional evaluation method and more in line with the actual situation.

The basic steps of action evaluation processes based on multidimensional adaptive entropy cloud models are as follows:

(1) According to the design requirements of normal cloud model, the quantitative domain of evaluation index $U = u_1, u_2, \cdots, u_i, \cdots, u_n$ is determined and the domain of evaluation index $C = C_1, C_2, \cdots, C_j, \cdots, C_n$ is constructed.

(2) Calculate the weight matrix of each indicator $W_{1\times n} = w_1, w_2, \cdots, w_n$ based on the cloud attention mechanism.

(3) After determining domains U and C, the evaluation domain's, C_j, value x_{ij} of each quantitative domain U_i has upper and lower bounds, and there is a bilateral constraint: x_{ij}^1 and x_{ij}^2. This evaluation domain is approximated by a cloud model within the bilateral constraint range. The calculation formula of cloud model parameters is determined by bilateral constraints, as shown in Formula (14). Finally, the characteristic parameter matrix $R = (Ex, En, He)_{ij}$ of the cloud model is established by domain U and domain L:

$$\begin{cases} E_{x_{ij}} = (x_{ij}^1 + x_{ij}^2)/2 \\ E_{n_{ij}} = (x_{ij}^1 + x_{ij}^2)/3, \\ H_{e_{ij}} = n \end{cases} \tag{14}$$

where n is a constant that is specifically adjusted according to the degree of fuzziness of the actual evaluation domain.

(4) After determining the cloud model's characteristic parameters, the normal cloud model affiliation matrix $Z_{n\times m} = Z_{ij}$ in the evaluation domain corresponding to the indicators of each cell is calculated by running the conditional cloud generator n times repeatedly and using a weighted average.

(5) According to the derived weight matrix W and the affiliation matrix Z, the affiliation subset $F_{1\times m} = W_{1\times n} Z_{n\times m}$ of the multidimensional adaptive entropy cloud model can be calculated.

(6) The obtained multidimensional adaptive entropy cloud model of the test action is placed in the same space with the multidimensional adaptive entropy cloud model generated based on the standard action features for comparison. First, the coordinate region where the cloud drops of the multidimensional adaptive entropy cloud model are more dense is obtained, and then the average affiliation, a, of the cloud drops of the multidimensional adaptive entropy cloud model generated based on the standard action features in this coordinate region is obtained.

(7) After obtaining average affiliation a, the score of action evaluation is calculated based on Formula (15):

$$Score = a \times 100 + b, \tag{15}$$

where b is the noise in the evaluation process, which changes with the scale of the action type to be evaluated.

The evaluation of operations related to grid operations in a virtual environment is finally completed after the above 7 steps. The process of action evaluation using a multidimensional adaptive entropy cloud-model-based action evaluation method to complete the action evaluation of wearing insulated gloves is shown in Figure 6.

Firstly, the quantitative domain of evaluation metrics $U_{1\times n}$ is determined based on the number of video frames, the domain of evaluation metrics $C_{1\times m}$ is constructed based on the number of types of action features, and the weight matrix $W_{1\times n}$ is calculated based on the cloud attention mechanism module. Then, n cloud drops are generated based on the cloud generator to obtain normal cloud model affiliation matrix $Z_{n\times m}$, and the normal cloud model affiliation matrix, $Z_{n\times m}$, and the weight matrix, $W_{1\times n}$, are used to obtain the affiliation subset, $F_{1\times m}$, of the multidimensional adaptive entropy cloud model; moreover, n affiliation subsets, $F_{1\times m}$, can obtain the corresponding multidimensional adaptive entropy cloud model. Finally, the cloud model is compared with the multidimensional adaptive entropy cloud model generated by the standard action in the same space, and the evaluation score of the action can be obtained.

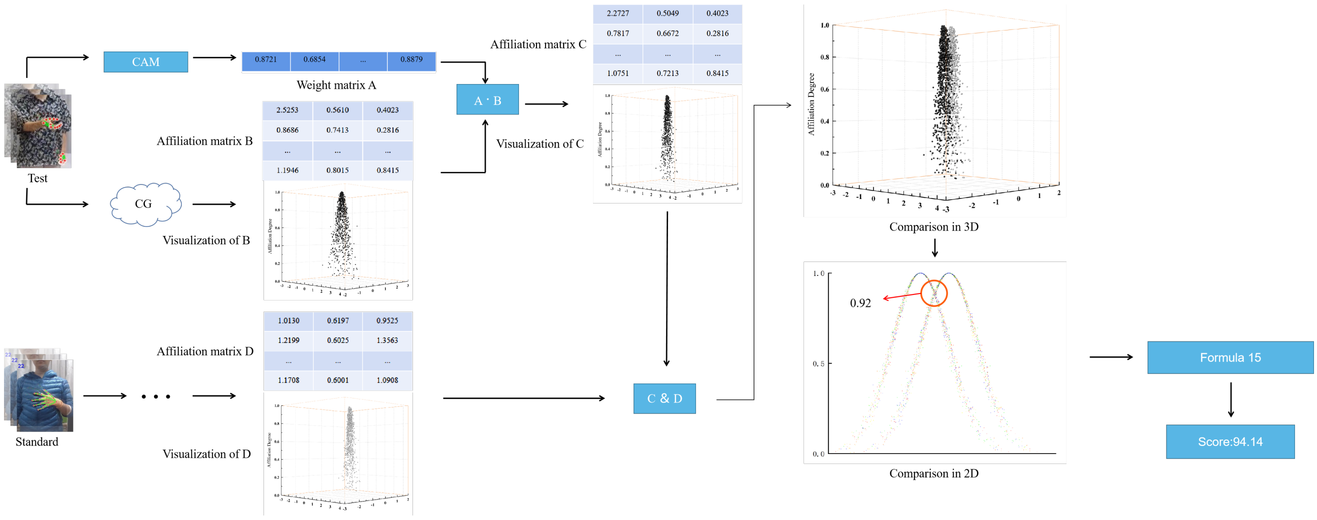

Figure 6. Evaluation process of wearing insulated gloves.

4. Application Instances

The mistakes in the operation of electric power operation will bring many risks, which can expose the operation that needs attention and improvement in the process of electric power operation. This paper repeats the actions that need to be trained in power operations and records the corresponding data for the evaluation of virtual actions. Operations in power operations include equipment wearing, electrical inspection, aerial work, etc. There are many fine operations, and matching them directly with standard actions and distinguishing subtle differences between them are difficult, so the evaluation of fine actions needs to be completed based on a multidimensional adaptive entropy cloud model. The flow of the action evaluation experiment is shown in Figure 7.

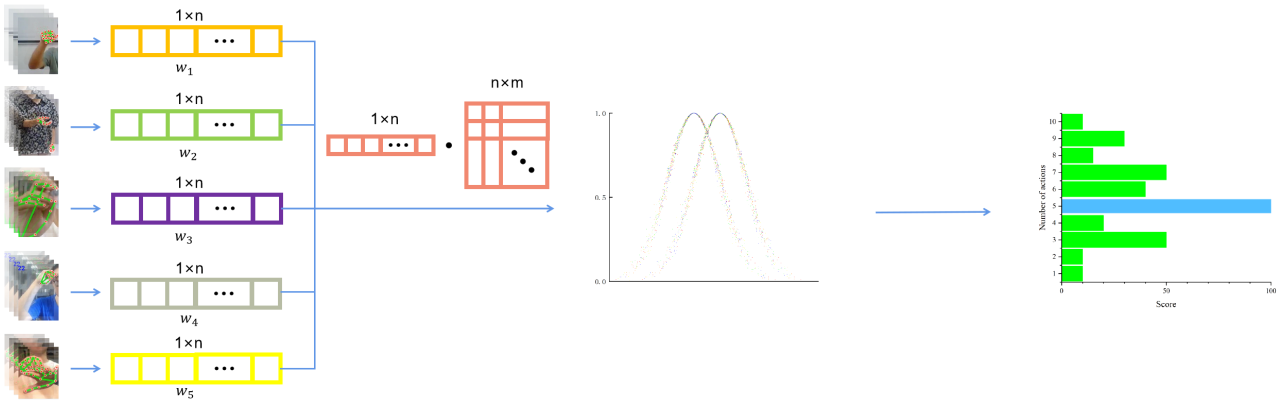

Figure 7. Experimental flow chart.

4.1. Data Acquisition and Processing

In order to obtain the standard multiscale data sets, 20 skilled operators were arranged to simulate a series of actions related to power grid operations, such as wearing a safety helmet, wearing insulated gloves, electricity testing, opening the door of the electrical box, screwing, etc. After excluding some invalid actions, a multiscale data set is constructed by using the multiscale hand action matrix. The specific distribution of each action in the original data set is shown in Table 1.

Each multiscale hand action matrix contains 20 frames, and each frame contains five fingertip speeds, four inter-finger distances, one palm position, and one wrist position. Then, the actual hand motion data obtained based on OpenCV technology are converted into a multiscale hand motion matrix, as shown in Figure 8.

Table 1. Action Distribution of the Original Data Set.

Action Type	Amount
Wearing safety helmet	89
Wearing insulated gloves	55
Electricity testing	89
Opening the door of the electrical box	120
Screwing	58

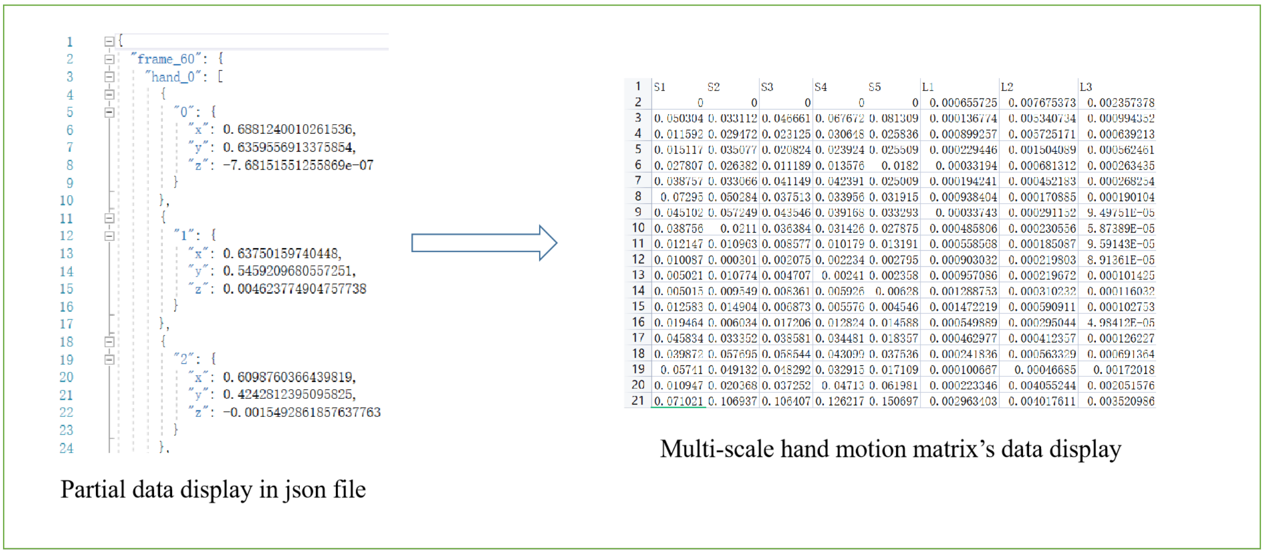

Figure 8. Action data conversion diagram.

From the data collected based on OpenCV, it can be seen that the data of each hand joint point comprises x, y, and z. The data are expressed in meters and represent 3D coordinates in the real world. An action datum in the action data set of wearing safety helmet is randomly selected, and the action of wearing a helmet is analyzed for the offset change on the z-axis.

Figure 9 above shows the offset change of the WRIST joint on the z axis. The curve conforms to the action process of wearing a helmet: grab the hat, pick up the hat, take the hat, and fix the hat. The action of wearing a safety helmet requires larger wrist motions and is a large-scale action.

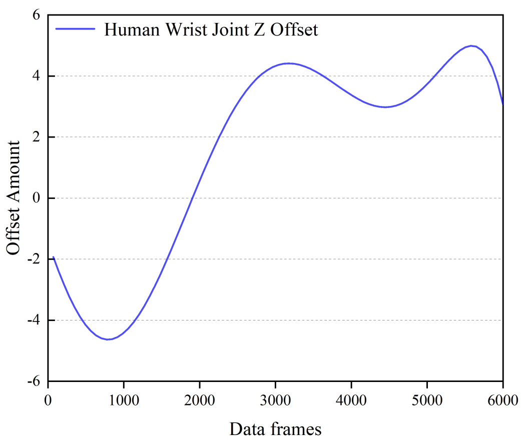

Figure 9. WRIST joint z axis offset curve.

4.2. Example of Action Evaluation

The operation in the power grid operation studied in this paper includes five types of actions: wearing a helmet, wearing insulating gloves, checking electricity, opening the electric box door, and twisting screws. The 4-step operation of wearing the helmet in a smart grid training system is shown in Figure 10.

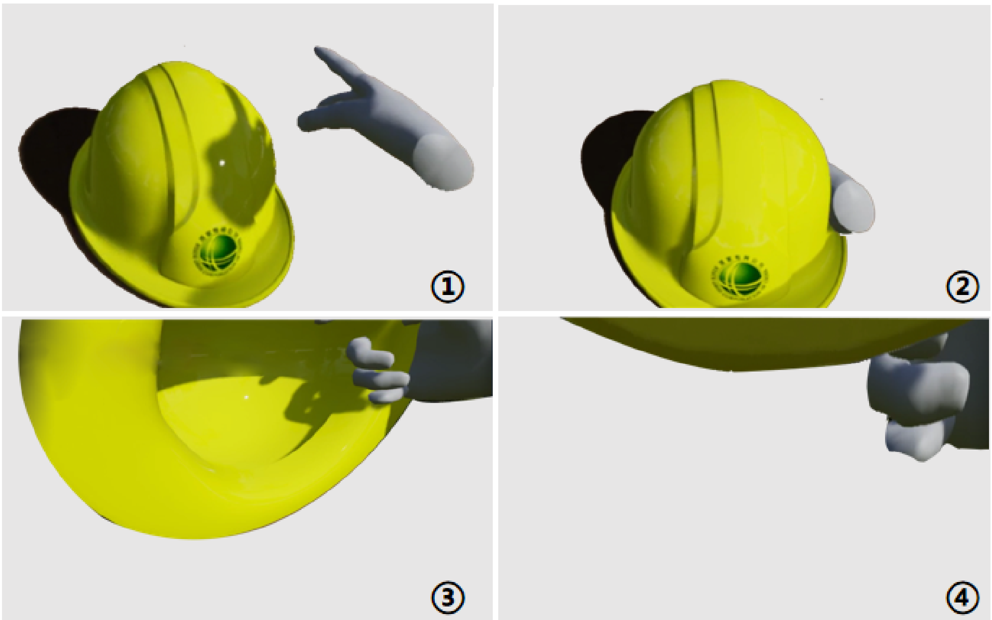

Figure 10. Operation of wearing helmet in a smart grid training system.

Based on the operation instructions and action of relevant technical personnel in electric power operations, experts analyze that when the wrist movement distance of an action is less than 1 cm, the finger joint data in the evaluation of the action should occupy a higher weight. When the movement of the wrist's distance is greater than 1 cm, the finger joints may be offset in all directions. When the offset angle is less than 30° and the offset distance is less than 1 cm, it can still be regarded as a motion that conforms to the operation change. Therefore, the data of the joint points of the palm and wrist should have higher weights during the action's evaluation.

Figure 11 shows a cloud model generated by a change in the movement characteristics of wearing a helmet. The coordinate region of dense cloud droplets with a membership degree that is greater than 0.9 can be seen roughly in the figure, showing common features of wearing a helmet. If no obvious error occurs during the operation, the cloud droplets generated based on the helmeted action's feature will gather in this coordinate area.

Due to lesser differences in the cloud model's features, which are generated based on the motion features of similar actions, the cloud attention mechanism will be used to highlight differences that exist before similar actions. Wearing helmets have been sorted the large-scale action, because the wrist movement distance is less than 1cm. The adaptive entropy weight matrix that conforms to large-scale motion characteristics is determined by the cloud attention mechanism. The multidimensional adaptive entropy cloud model is constituted by new cloud droplets that are generated by weights in the adaptive entropy weight matrix and each cloud droplet in the cloud model.

As shown in Figure 12, the multidimensional adaptive entropy cloud model that is generated by the standard motion feature is represented by purple; meanwhile, another cloud model generated by the test motion feature is represented by gray. The chart clearly reveals a large difference betweenthe two multidimensional adaptive entropy cloud models generated by similar actions; the coordinate region with denser gray dots is the coordinate region with a membership of about 0.8 in the purple cloud model.

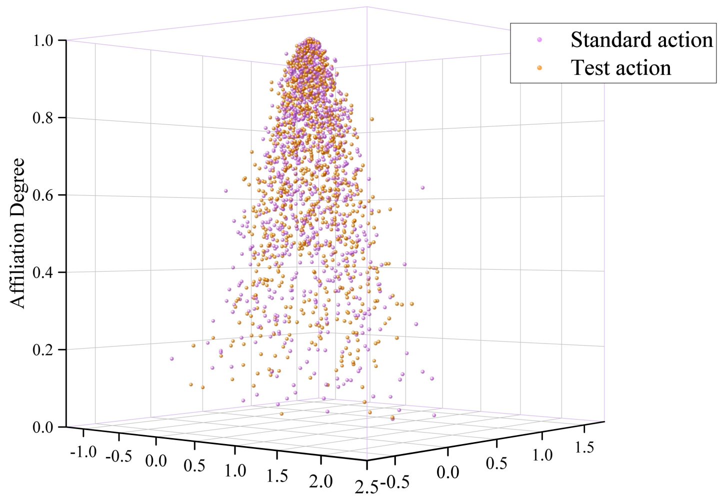

Figure 11. Cloud model containing action features of wearing a safety helmet.

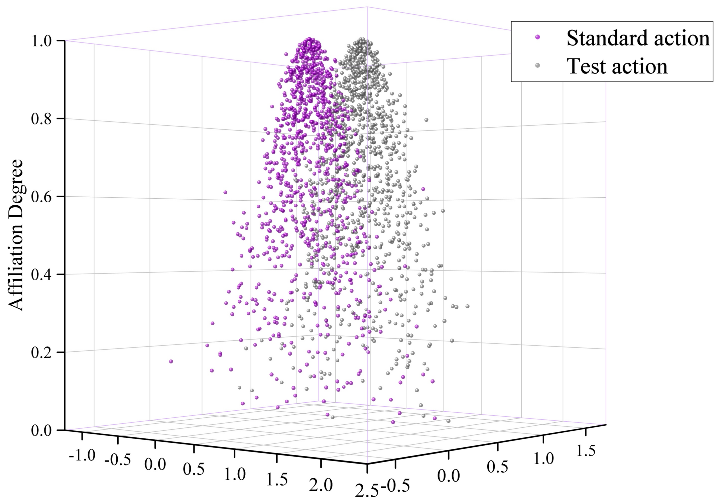

Figure 12. Multidimensional adaptive entropy cloud model comparison diagram of the test action and standard action.

According to calculation, the average membership degree of blue cloud droplets in this coordinate region is 0.8468.

4.3. Experiments and Result Analysis

In order to verify the reliability and feasibility of grid-related actions evaluation method based on a multidimensional adaptive entropy cloud model, the expert evaluation score and the action evaluation score based on DTW (Dynamic Time Warping) are set as control experiments. The action evaluation module in the smart grid training system is used as the experimental object, the actions of the experimental personnel are evaluated in the laboratory, and the feasibility of the method is determined by recording the evaluation scores of the three methods.

Based on the idea of dynamic programming, the DTW algorithm is used to judge similarities between temporal data. DTW can compare two sequences of different lengths by representing the same type of data after time normalization. The distance between every two points between the two sequences is calculated using Euclidean distances, and the shortest distance for evaluating the similarity between the two sequences is finally obtained. DTW has been widely used in the field of audio processing, and it is currently also applied to action evaluation [31]. By comparing the change curves of the rotation angles of the wrist nodes of the standard action and the test action, the shortest distance between the curves was calculated, and the similarity between the standard action and the test action was judged to complete the evaluation of the action.

Using expert grading, action evaluations based on DTW; grid-related action evaluation methods based on a multidimensional adaptive entropy cloud model; and the five types of actions, including wearing helmets, wearing insulated gloves, electroscope, opening the door of the electric box, and tightening the screws are evaluated. Each type of action is evaluated three times, and the evaluation results are shown in Table 2.

Table 2. Action distribution of multiscale hand data set.

	Experts' Comments	**Action Evaluation Based on DTW**	**Grid-Related Actions Evaluation Method Based on Multidimensional Adaptive Entropy Cloud Model**
Wearing safety helmet 1	95.50	97.83	93.37
Wearing safety helmet 2	93.50	85.22	91.39
Wearing safety helmet 3	91.00	86.54	88.63
Wearing insulated gloves 1	97.50	96.28	98.75
Wearing insulated gloves 2	96.50	37.35	91.96
Wearing insulated gloves 3	96.50	98.35	93.87
Electricity testing 1	97.50	97.85	90.25
Electricity testing 2	60.00	97.26	73.25
Electricity testing 3	91.50	97.61	86.46
Opening the door of the electrical box 1	100.00	98.58	91.68
Opening the door of the electrical box 2	99.00	99.65	97.55
Opening the door of the electrical box 3 Screwing 1	99.50 95.00	99.24 86.12	86.94 95.52
Screwing 2	90.00	93.57	96.33
Screwing 3	99.00	96.74	90.24

It can be seen from Table 2 that the expert score may ignore the subtle differences, and it is usually subjective. The action does not have obvious error scores above 90 points, and the one-time error score will be as low as 60. The action evaluation based on DTW is effective in scoring large-scale actions, but it cannot score fine actions. For example, the scores of the electroscope actions are roughly the same, and they will be affected by invalid actions. It is impossible to score sequential actions. For example, the standard action of wearing insulated gloves is to wear insulated gloves with the left hand first, and wearing insulated gloves with the right hand first obtains a low score. The grid-related actions evaluation method based on a multidimensional adaptive entropy cloud model overcomes the subjectivity of expert scoring, and it is not affected by invalid operations. It can evaluate actions of any scale in more detail. It is proved that the grid-related action evaluation method based on a multidimensional adaptive entropy cloud model can be applied to smart grid training systems, and the evaluation score of this method is effective and objective. It is proved that grid-related actions evaluation methods based on a multidimensional adaptive entropy cloud model can be applied to smart grid training systems, and the evaluation score of this method is effective and objective.

5. Discussion

Most current studies only evaluate the stability and communication efficiency of smart grid training systems, but they rarely examine the content and functionality in smart grids [32,33]. Aiming at solving the issue of the paucity of research evaluating power grid operation-related actions, this paper proposes an evaluation method of grid-related actions based on a multidimensional adaptive entropy cloud model for the evaluation of fine actions in the power grid's operation process.

Currently, most action evaluation models take the accuracy and loss function of action recognition as the main basis for action evaluation. These methods are not accurate enough in the description of action features, and it is easy to ignore subtle differences between the same actions [34,35]. This paper proposes a cloud attention mechanism that can be used to extract features of different scales in multiscale data sets to construct an adaptive entropy weight matrix to improve the completeness of hand motion representations in the cloud model. The multidimensional adaptive entropy cloud model constructed by the adaptive entropy weight matrix and the basic cloud model can obviously show the subtle difference between actions. The obtained multidimensional adaptive entropy cloud model is compared with the multidimensional adaptive entropy cloud model based on the standard action feature generation in the same space to obtain the evaluation level of the hand action. Finally, the feasibility of the method is verified by experiments. Compared with the existing literature, this paper not only evaluates whether the action is correct but also provides a specific score on the fine operation of power grid operations.

The evaluation method of grid-related actions based on a multidimensional adaptive entropy cloud model proposed in this paper is theoretically applicable to most action evaluations, but it has higher requirements for accuracies in obtaining action-related data and the correlation of extracting action features. The model proposed in this paper can be applied to most systems that need to evaluate actions if the action data can be accurately acquired and the features that can accurately describe the motion of the action can be extracted.

6. Conclusions

In order to evaluate grid-related actions, this paper proposes an evaluation method of grid-related actions based on a multidimensional adaptive entropy cloud model. Firstly, the cloud attention mechanism was used to objectively determine the adaptive entropy weight matrix so as to construct a multidimensional adaptive entropy cloud model that enables the cloud model to represent the characteristics of the same type of action from different scales. Then, the evaluation level of this hand action is obtained by comparing the obtained multidimensional adaptive entropy cloud model with the multidimensional adaptive entropy cloud model generated based on the standard action characteristics in the same space, and this evaluation result is objective and effective.

In application instances, this paper evaluates five types of grid operation-related actions, including wearing safety helmets, wearing insulated gloves, electricity testing, opening the electrical box door, and screwing during grid operations with electricity. The evaluation results are compared with experts' evaluation and DTW-based action evaluation, and the data show that the evaluation method based on a multidimensional adaptive entropy cloud model is more objective than experts' evaluation, and the evaluation results are more effective than DTW-based action evaluations because it can show the characteristics of fine actions from different scales. Therefore, the multidimensional adaptive entropy cloud-model-based action evaluation method can be applied to the evaluation of fine actions in the process of grid operations.

In the future, more comprehensive motion features, such as temporal features, etc., that can be further incorporated when constructing the adaptive entropy weight matrix can be used to improve the performance of the evaluation method of grid-related actions based on the multidimensional adaptive entropy cloud model. In addition, the method can be subsequently applied to more fine actions relative to smart grid training systems, and the characteristics of different actions can be in-depth analyzed to further improve the action evaluation model.

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