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Article

Research on aerobics action modal recognition algorithm based on fuzzy system and reinforcement learning

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Abstract: Nowadays, human movement recognition technology has received a high degree of attention and has been used in a variety of fields such as intelligent security and motion analysis. The traditional action recognition method relies on artificial extraction of features, not only the recognition efficiency is low, and the recognition accuracy is not high, has been unable to meet the requirements of action recognition. The action recognition method based on reinforcement learning can automatically extract features, greatly simplifying the process of manual feature extraction in the traditional method, but at the same time, it also has some defects such as easy to be disturbed by external environment and complicated network training. In view of this situation, this paper takes aerobics action recognition as an example, proposes an action recognition algorithm based on Fuzzy least squares support vector machine, and adopts Fuzzy LS-SVM classification algorithm to realize the classification of actions on the feature set. The results of the study show that the aerobics movement recognition algorithm proposed in this paper has more excellent performance compared to the traditional recognition algorithms.

Keywords: fuzzy system; reinforcement learning; aerobics movement recognition; Fuzzy LS-SVM; set empirical modal decomposition

1. Introduction

As a major research direction in the field of machine learning, human action recognition has achieved many research results in recent years, which has good prospects and important practical significance. In the beginning of the development of action recognition technology, mainly through the artificial way of data feature extraction,nowadays, with the expansion of the scale of data, the popularity of high-performance computing equipment and the development of neural network technology, the use of deep reinforcement learning to replace the traditional artificial feature extraction has become a mainstream trend. Compared with manual feature extraction, deep reinforcement learning can be used to automatically extract features and process large-scale data. In addition, deep reinforcement learning has strong learning ability, rich high-level semantic information and good portability. Therefore, action recognition methods based on deep reinforcement learning have become a current research hotspot.

In the aspect of action recognition research, Banos [1] adopted the idea of hierarchical weighting and combined with traditional classifiers to identify 9 typical daily actions, achieving a recognition accuracy of more than 95%. Schmid [2] improved on the basis of DT and proposed IDT (Improve Dense Trajectory). By optimizing the optical flow graph, the feature regularization mode was improved, and Fisher Vecor was used to improve the algorithm performance. Andonian [3] proposed a Temporal Relation Network (TRN) based on TSN, which can understand and judge the temporal dependence problems at various scales in video images and video frame sequences, improving the overall efficiency of the network. Kipf [4] uses Graph Convolutional Network (GCN) to represent human nodes by graph nodes and limbs by graph edges, and identifies actions through graph convolutions. Si [5] combines GCN and LSTM, uses GCN to capture the spatial information between the key points of the skeleton, and then uses LSTM to conduct feature modeling for the features of the key points in time dimension to realize action recognition.

In terms of aerobics movement recognition research, Chen [6] proposed an aerobics jump feature extraction method based on MIM-LBP. The method projected the depth video sequence in the Cartesian plane, divided the video sequence, obtained several time series with the same energy, calculated their corresponding depth motion graph energy, and established the motion energy model according to the calculation results. Based on the LBP descriptor, the motion energy model was encoded to extract the effective information of aerobics jumping movements, and finally the information was input into the classifier to complete the feature extraction of aerobics jumping movements. However, this method did not extract the key frames of aerobics videos and could not accurately identify the movement orientation Angle, resulting in a low feature extraction rate. Feng [7] proposed an image-based method for aerobics movement accuracy monitoring. Kinect depth image acquisition method was used to conduct pre-analysis of aerobics movements, and HOG3D was used to extract aerobics movement features. This method effectively reduces the energy consumption of aerobics movement precision monitoring, but the perception of movement trajectory is not comprehensive and the accuracy is low.

It can be seen from the collation and induction of the above related literature on movement recognition that the current research on movement recognition using deep reinforcement learning has achieved fruitful results. However, it can also be seen that most of the current recognition algorithms have incomplete perception of movement trajectory, low accuracy rate and complicated recognition process, resulting in high energy consumption [8]. The current recognition algorithms have the defects of insufficient practicability. Based on this, this paper proposes a Fuzzy LS-SVM classifier to identify the aerobics action algorithm, by using equality constraints instead of inequality constraints, the algorithm avoids the time-consuming quadratic programming problem, and solves the problem of long training time of support vector machine.

The research innovation of this paper is as follows: in the feature selection algorithm, the sparse multinial logistic regression algorithm with Bayesian regularisation (SBMLR) algorithm is innovatively used in the action recognition. This algorithm is an embedded selection algorithm, with high recognition rate and relatively low computational complexity [9]. In terms of classification algorithm, starting from the traditional support vector machine with relatively high classification accuracy, the paper analyzes its defects in training time, computation amount, and the phenomenon of inseparable region when extended to multi-class problems, and puts forward a fuzzy least squares support vector machine classification algorithm that can solve these two problems well. By using equality constraint instead of inequality constraint, the algorithm avoids the time-consuming quadratic programming problem and solves the problem of long training time of support vector machine. By introducing fuzzy membership function, the inseparable region in multi-class problems is well eliminated.

2. Feature selection algorithm based on SBMLR

SBMLR is a gene selection algorithm originally used for cancer classification, The selection algorithm is an embedded selection algorithm based on sparse polynomial logistic regression. Set the training sample set as $D = \{(x^n, t^n)\}_{n=l}^{l}$, X is the NTH input feature vector, t^n is the corresponding expected output vector [10]. Since this method is to solve multi-class problems, the common 1 encoding scheme for c is represented, where c is the class number. Polynomial logistic regression uses soRmax inverse join function to build a generalized linear model, so that the output is expressed as a probabilistic prior estimate of the class members, the expression is:

$$p(t_i^n|x^n) = y_i^n = \frac{exp\{a_i^n\}}{\Sigma_{j-l}^{c} \exp\{a_j^n\}}, a_i^n = \sum_{j=l}^{d} w_{ij} x_j^n \tag{1}$$

Set D to represent an independent set of equally distributed samples from a conditional polynomial distribution, then the negative log-likelihood function as a measure of data mismatch can be expressed as:

$$E_D = \sum_{n=l}^{l} E_D^n = -\sum_{n=l}^{l} \sum_{i=l}^{c} t_i^n \, log\{y_i^n\} \tag{2}$$

The parameter w of the polynomial logistic regression can be found by maximizing the likelihood of the training sample, or equivalent minimizing the negative log-likelihood logarithm of the training sample [11]. However, the model thus generated is completely compact, and strictly speaking none of the elements of the model parameter w are exactly zero. Ideally, the desired model is based on the small set of features that contain the most information, and the excess features will be pruned away from the model. Sparse models can be introduced by adding regularization terms to the negative log-likelihood function E_D. Thus, the estimate of the parameter w is given by minimizing a maximum likelihood training criterion with a penalty coefficient:

$$L = E_D + \alpha E_w, E_w = \sum_{i=l}^{c} \sum_{j=l}^{d} |w_{ij}| \tag{3}$$

In the formula, α is the normalizing parameter that controls the balance of the bias variance, and at a minimum point of L.

2.1. Eliminate the regularization parameter

In the Bayesian frame, a better regularization parameter estimation can be obtained by integrating [12]. The prior distribution of the model parameters can be marginalized by alpha to get:

$$p(w) = \int p(w|\alpha)p(\alpha)d\alpha \tag{4}$$

Since α is a scaling parameter, using Jeffrey's prior distribution as an unreal prior distribution representing no knowledge of the regularized parameter α, corresponding to the assumption that Logα is uniformly distributed, we get:

$$p(w) = \frac{1}{2^W}\frac{\Gamma(W)}{E_w^W} \Rightarrow -\log p\,(w) \propto W \log E_w \tag{5}$$

The optimized criterion modified by sparse logistic regression based on Bayesian regularization can be obtained as follows:

$$M = E_D + W \log E_w \tag{6}$$

It can be seen that the regularization parameters have been eliminated in the formula.

2.2. Specific implementation

Minimization of the training criterion incorporating the Bayesian regularization method can be obtained by a simple modification of the extant cyclic coordinate descent algorithm for sparse regression using the Laplace prior [13]. Differentiation of the original training criterion and the modified training criterion are obtained separately:

$$\nabla L = \nabla E_D + \alpha \nabla E_w \tag{7}$$

$$\nabla M = \nabla E_D + \tilde{\alpha} \nabla E_w \tag{8}$$

From the point of view of the gradient descent algorithm, minimizing M is actually equivalent to minimizing L, assuming that the regularization parameter α is constantly updated to track every change in the model parameter w, so that only very small modifications are required to the existing sparse logistic regression training algorithm, due to the elimination of the unique training parameter, Thus eliminating one of the model selection processes when training the model.

3. Action recognition algorithm based on fuzzy least squares support vector machine

The process of movement recognition for aerobics can be roughly divided into three steps: the first step is the feature extraction of movement signals, that is, the use of appropriate feature extraction methods to extract the distinguishing features from the movement signals of aerobics; The second step is feature selection. Since there are redundant features in a large number of features extracted, it is necessary to use appropriate feature selection algorithm to get the most favorable feature subset for classification; The third step of action classification recognition, that is, the feature selected in the second step is created into a feature set, the feature set is trained to get a classifier, and finally the classifier is used for classification [14]. It can be seen that how to design the classifier scientifically and reasonably has become the key to the recognition of aerobics actions. Based on this, this paper presents a classifier design algorithm based on fuzzy least squares support vector machine.

3.1. LS-SVM

In essence, LS-SVM (Least Squares Support Vector Machine) is an extended form of SVM, inheriting the basic idea of SVM, but LS-SVM uses the equality constraints rather than inequality constraints, and the second-paradigm number of errors is chosen as the cost function, which makes the problem solving process greatly simplified [15]. In this way the solution process of LS-SVM is transformed into solving a linear programming problem, and the methods that can efficiently solve such problems are iterative methods such as the conjugate gradient method. Compared with SVM, the optimization problem of LS-SVM replaces inequality constraints with equality constraints, and the time-consuming quadratic programming problem is transformed into a simple linear programming problem. When the data volume of the training samples is large, the SVM solution process requires large computational resources and the training time is relatively long. The reason is that the optimization problem of SVM is a quadratic programming problem with inequality constraints, and when the data volume of training samples is large, the computational complexity of solving the problem is very high, which usually requires a lot of computational resources and time. On the other hand, LS-SVM transforms the quadratic programming problem into a linear system of equations problem by replacing the inequality constraints of SVM with equality constraints, so its solution process is relatively simple and the computational complexity is low. Since LS-SVM solves a set of linear equations, it requires less computational resources and the training speed is accelerated accordingly.

For LS-SVM, the optimization problem becomes:

$$min J_2 (w, b, e) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{k=1}^{N} e_k^2 \tag{9}$$

After optimization with optimization conditions, the original problem can be transformed into a linear problem:

$$\left[\frac{0}{Y} \middle| \frac{-Y^T}{ZZ^T + \gamma^{-1} I}\right] \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \tag{10}$$

Therefore, the establishment of the classifier can be obtained by linear equation.

3.2. Fuzzy LS-SVM

In one-to-many SVMs algorithm, a k-class problem is converted into k two-class problems and the ith two-class problem is to separate class i from the rest of the classes. To solve this problem a fuzzy function can be introduced. Based on this, this paper proposes a Fuzzy LS-SVM, i.e., on the basis of LS-SVM, an affiliation function is defined for each class by introducing a fuzzy function.

Given a training sample $\{x_k, y_k\}_{k=1}^{N}$, x_k is the input sample and y_k is the output, the optimal problem of LS-SVM is:

$$min\,J_2\,(w,b,e) = \frac{1}{2}w^T w + \gamma \frac{1}{2}\sum_{k=1}^{N} e_k^2 \tag{11}$$

$$st.\,y_k[w^T\phi(x_k) + b] = 1 - e_k \tag{12}$$

Set the LS-SVM$_{ij}$ binary classifier used to separate class i and class j, and its corresponding decision function is:

$$G_{ij}(x) = w_{ij}^T\phi(x) + b_{ij} \tag{13}$$

To calculate the sample x of the classification:

$$G_i(x) = \sum_{j\neq 1, i=1}^{k} sign(G_{ij}(x)) \tag{14}$$

Finally categorize the sample as:

$$\underset{i=1,\ldots,k}{arg}\; max\,G_i\,(x) \tag{15}$$

If the above equation is satisfied by only one i, then x is classified into class i. If more than one i satisfies the condition, then x is indivisible [16]. The indivisible region for one-to-one classification is shown in **Figure 1** below.

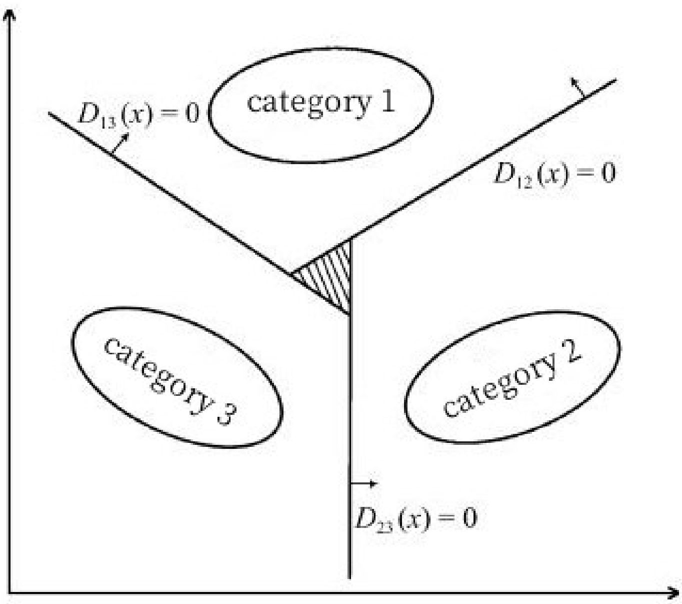

Figure 1. Categorizes indivisible regions one-to-one.

In order to avoid this problem, this paper introduces fuzzy function. Firstly, the one-dimensional membership function perpendicular to the optimal classification hyperplane D_{ij} is defined as $m_{i,ij}$, which is used to express the membership degree of x belonging to class i under the classifier LS-SVM$_{ij}$:

$$m_{i,ij}(x) = \begin{cases} 1, G_{ij}(x) \geq 1 \\ G_{ij}(x), other \end{cases} \tag{16}$$

The minimum fuzzy operator is used to define the membership function of $m_i(x)$ in all relevant classifiers that the sample x to be classified belongs to class i, can be obtained $m_i(x) = min\, m_{i,ij}\,(x)$.Using the minimum fuzzy operator, the shape of the affiliation function in the feature space is a truncated prismatic polyhedron, and the isosurfaces are parallel to the decision function. This is shown in **Figure 2** below.

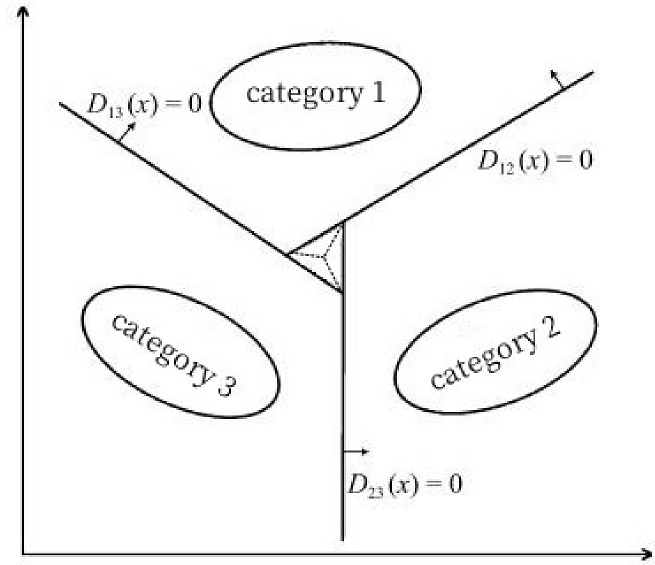

Figure 2. The minimum fuzzy operator solves the unclassifiable region.

3.3. Aerobics action recognition based on Fuzzy LS-SVM algorithm

Calisthenics as a collection of fitness, entertainment and competition in one of the sports, its movement mode recognition for improving the training effect, to ensure the health of athletes is of great significance. The traditional method of aerobics movement recognition mainly relies on manual observation and manual annotation, which has some problems such as strong subjectivity and low efficiency. Therefore, this paper puts forward a new calisthenics action modal recognition algorithm based on Fuzzy LS-SVM.

(1) The extracted features are further screened using the SBMLR algorithm to obtain a subset of features with lower dimensionality but higher discriminative power.
(2) Based on the filtered feature subset, the Fuzzy LS-SVM model is constructed, and the parameters of the Fuzzy LS-SVM model are optimized using the particle swarm optimization algorithm to improve the recognition performance of the model.
(3) For input x to calculate the output of each LS-SVMs, $G_{ij}(x) = w_{ij}^T \phi(x) + b_{ij}$
(4) According to the membership calculation formula $m_{i,ij}(x)$, and then according to the calculated results, the following matrix is constructed:

$$M = \begin{bmatrix} 0 & m_{1,12} & m_{1,13} & \cdots & m_{1,1k} \\ m_{2,21} & 0 & m_{2,23} & \cdots & m_{2,2k} \\ m_{3,31} & m_{3,32} & 0 & \cdots & m_{3,3k} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ m_{(k-1),(k-1)1} & m_{(k-1),(k-1)2} & m_{(k-1),(k-1)3} & \cdots & m_{(k-1),(k-1)k} \\ m_{k,k1} & m_{k,k2} & m_{k,k3} & \cdots & 0 \end{bmatrix} \tag{17}$$

(5) Calculate the value of each row mi(x) of the matrix, and obtain the column vector MR:

$$fori = 1\!: k$$

$$m_i(x) = min\, m_{i,ij}\,(x) \tag{18}$$

$$\Rightarrow MR = [m_1(x), m_2(x), .., m_k(x)]^T$$

(6) Find the largest element in *MR*, *denoted*$_{max}$ as MR_{max}, and if MR Is subscript *i* in *MR*, divide *x* into *class i*.

4. Experimental analysis

4.1. Experimental data

The aerobics movement database selected in this experiment is of two different types, one of which is the aerobics movement database of many people, which is marked as database A in this paper [17]. The other database is the individual instructional calisthenics movement breakdown database, which is labeled as database B in this article. Database A contains 180 calisthenics videos that were shot in a variety of locations, both indoor and outdoor, and partially covered. Database B contains a video breakdown of an aerobics instructor, totaling 68 videos. The video resolution in both databases is 960 × 720 pixels.

4.2. SBMLR feature selection algorithm effect analysis

SBMLR feature selection algorithm is an embedded feature selection method, which combines the advantages of high execution efficiency of filter model and high recognition accuracy of package model. In this experiment, the SBMLR feature selection algorithm is compared with ReliefF and T-test, which are commonly used feature selection algorithms. Fuzzy LS-SVM algorithm is used as classifier, and EEMD energy feature is used as feature vector.

(1) Feature vector selection

In the experiment, 96-dimensional feature vectors based on EEMD features were used. In the data segmentation stage, the length of sliding window was also set to 2.5s, and each observation window contained the motion signals of all 4 data links. There was 50% data overlap between adjacent observation Windows. Since only the first few IMF components obtained by EEMD contain the main information of the signal, the energy of the first 4 IMF components of each axis signal of all 4 groups of motion data in the observation window is extracted as the feature in the experiment, and the dimension of the generated feature vector is 96.

(2) Evaluation methods

In order to have a unified performance evaluation standard, the identification method proposed in this study was verified by the leave-one cross-validation method in the experiment. The so-called leave-one cross-validation method means that the training set used in training the classifier is the data from all subjects remaining after the exclusion of one subject, and then the data of the excluded object is used for testing. This process is repeated until every single piece of data has been used as the test dataset once [18]. With this method, the total accuracy is calculated for each repetition of the training. The average of the test classification results obtained during the testing process. This verification method can better highlight the robustness of the data classification algorithm for different experimenters.

(3) Experimental results

Firstly, the aerobics movements were classified, and 7 movements including upward stretching, downward stretching, chest crossing, fist locking, stepping, leg swinging and stepping were selected for experimental verification. The recognition accuracy of each movement and the average recognition accuracy under different feature algorithms were shown in **Table 1** below.

Table 1. Recognition accuracy rate.

Action Accuracy Method	**ReliefF**	**T-test**	**Fuzzy LS-SVM**
upstretch	94.29	97.14	95.36
Stretch down	98.88	99.64	100.0
Chest Cross	89.64	93.93	94.29
Fist Hold	93.57	96.07	96.79
Take a step	90.71	80.71	86.79
Leg swing	86.43	92.14	88.21
Step	92.14	94.29	97.50
average	92.24	93.42	94.13

It can be seen from the data in the table that the SBMLR feature selection algorithm used in this paper is superior to other algorithms. Moreover, the feature dimensions obtained by the other two feature selection algorithms are higher than those obtained by SBMLR algorithm, which increases the complexity of classifier training in the latter stage to a certain extent. This can also explain the superiority of the SBMLR feature selection algorithm used in this paper.

4.3. Analysis of aerobics action recognition effect based on Fuzzy LS-SVM algorithm

Select the up stretch, chest cross, down stretch and fist calisthenics decomposition action in database B, respectively using decision tree, LS-SVM and Fuzzy LS-SVM algorithm for recognition, the recognition results obtained are shown in **Figures 3–5** below.

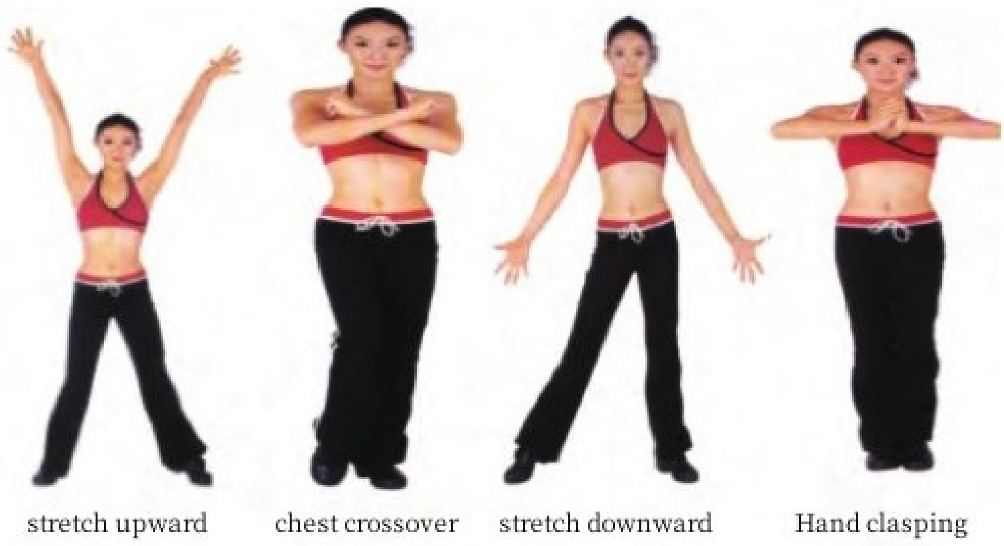

Figure 3. Fuzzy LS-SVM algorithm.

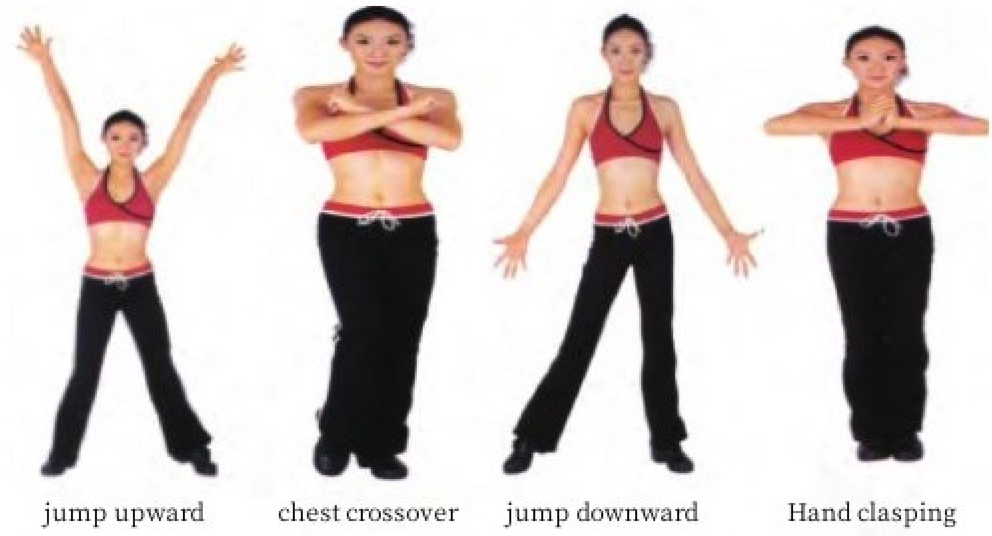

Figure 4. Decision tree algorithm.

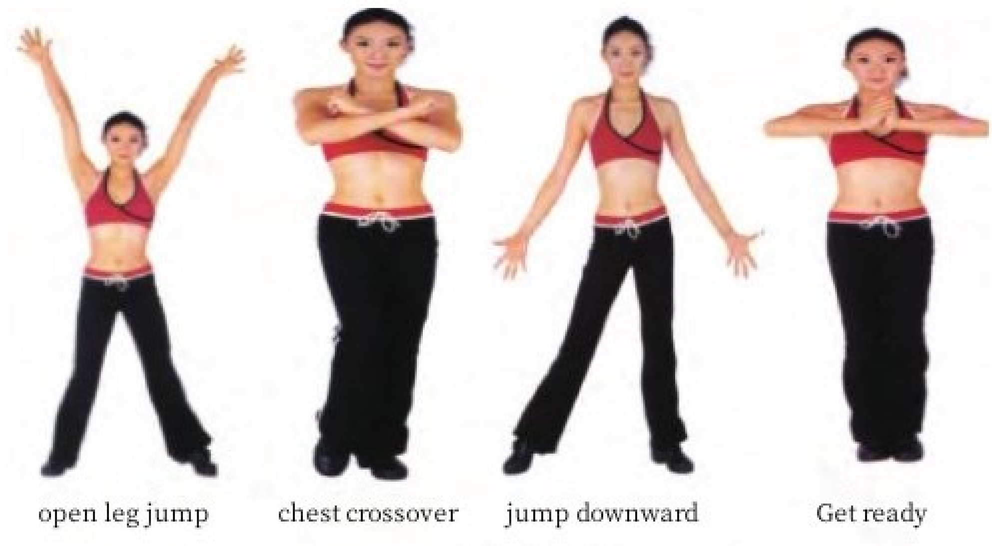

Figure 5. LS-SVM algorithm.

It can be seen that this paper's method has the most accurate recognition results for aerobics decomposition movement images, which can effectively recognize various aerobics decomposition movements, while the other two methods have some errors in the recognition results, which also verifies that the proposed method in this paper has a high degree of recognition accuracy.The reason for this is that the decision tree algorithm is relatively weak in handling noisy data and complex relationships, resulting in low classification accuracy, which affects the recognition effect.The LS-SVM algorithm is excellent in handling high-dimensional data and complex relationships, with high classification accuracy, but at the same time, due to its high sensitivity to the parameters, the selection of parameters has a great impact on the classification effect, and the performance is not stable enough. The Fuzzy LS-SVM algorithm constructed in this paper, on the other hand, handles the uncertainty in the data by introducing the fuzzy affiliation function, improves the robustness and generalization ability of the model, and has a better performance compared with the LS-SVM algorithm.

To further validate the performance of the methods in this paper, the database B is validated using leave-one-out cross-validation method, where part of the data in the database is randomly selected as test data and the rest as training data. The resulting confusion matrices for the three methods to recognize database B are shown in **Tables 2–4** below.

Table 2. Fuzzy LS-SVM algorithm identifies confusion matrix for database B.

	Stretch up	**Stretch down**	**Chest cross**	**Fist lock**	**Step**	**Leg swing**	**Step**
upstretch	100	0	0	0	0	0	0
Stretch down	0	100	0	0	0	0	0
Pectoral cross	0	0	95.8	4.2	0	0	0
Fist Hold	0	0	3.6	96.4	0	0	0
Take a step	0	0	0	0	100	0	0
Swing leg	0	0	0	0	0	100	0
step	0	0	0	0	0	0	100

Table 3. Decision tree algorithm identifies confusion matrix for database B.

	Stretch up	**Stretch down**	**Chest cross**	**Fist lock**	**Step**	**Leg swing**	**Step**
upstretch	100	0	0	0	0	0	0
Stretch down	0	100	0	0	0	0	0
Pectoral cross	0	0	93.8	6.2	0	0	0
Fist Hold	0	0	4.7	95.3	0	0	0
Take a step	0	0	0	0	91.8	3.7	4.5
Swing leg	0	0	0	0	2.8	94.3	2.9
step	0	0	0	0	5.1	4.3	91.6

Table 4. LS-SVM algorithm for identification of confusion matrix in database B.

	Stretch up	Stretch down	Chest cross	Fist lock	Step	Leg swing	Step
upstretch	100	0	0	0	0	0	0
Stretch down	0	100	0	0	0	0	0
Pectoral cross	0	0	91.6	8.4	0	0	0
Fist Hold	0	0	7.2	92.8	0	0	0
Take a step	0	0	0	0	93.1	1.2	5.7
Leg Swing	0	0	0	0	0	100	0
step	0	0	0	0	5.3	0	94.7

The horizontal comparison analysis shows that this paper's method has the lowest level of confusion in recognizing the decomposition movements of aerobics, the decision tree recognition algorithm will confuse the chest-crossing movement with the holding movement, the stride movement swinging leg movement and the stepping movement, and the LS-SVM algorithm will confuse the chest-crossing movement with the holding movement, the stride movement and the stepping movement.

Decision tree, LS-SVM and Fuzzy LS-SVM algorithms were used to recognize the aerobics decomposition movements in database A. The results of the comparison of the recognition accuracies of the three methods under low light conditions, indoor scenes and outdoor scenes are shown in **Figure 6** below.

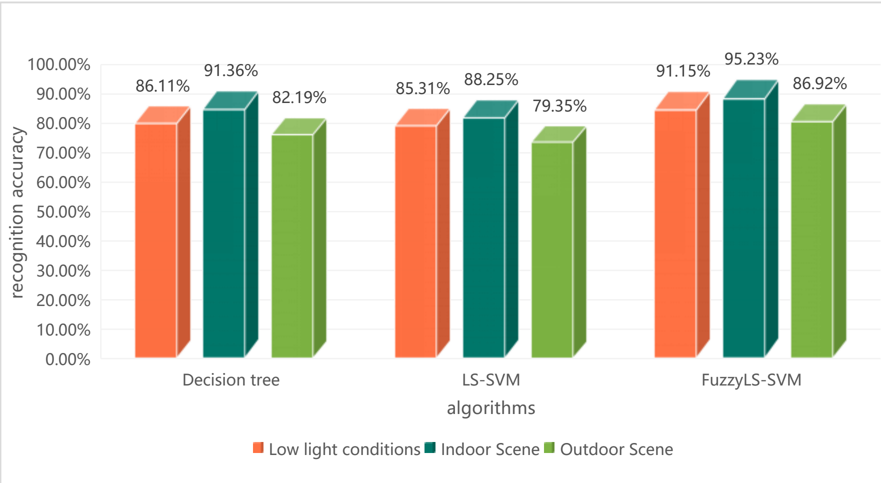

Figure 6. The recognition accuracy of the three algorithms in different scenes.

As seen from the data in the figure, the recognition accuracies of this paper's method for different scenarios are 91.15%, 95.23% and 86.92%, which are all higher, further verifying that this paper's method has higher accuracy compared to the other two methods.

5. Conclusion

In particular, it is worth noting that in the context of sports power, the application of action recognition and evaluation to sports action has become a trend, this paper in the feature algorithm innovative SBMLR algorithm used in action recognition, the algorithm is an embedded selection algorithm, with high recognition rate and relatively low computational complexity characteristics. In terms of classification algorithm, starting from the traditional support vector machine with relatively high classification accuracy, the paper analyzes its defects in training time and computation amount, as well as the phenomenon of inseparable region when expanding to multiple classes of problems, and puts forward a fuzzy least squares support vector machine classification algorithm that can solve these two problems well. Based on this foundation, a new aerobics action recognition algorithm based on Fuzzy LS-SVM is built. Finally, the aerobics movement recognition algorithm proposed in this paper is tested experimentally, and the results of the study show that the algorithm in this paper has more excellent recognition performance compared to the traditional decision tree algorithm and LV-SVM algorithm.

Although an aerobics movement recognition algorithm is given in this paper and verified to have good recognition accuracy, the feature selection algorithm used in this paper is not satisfactory enough for some movements. In this regard, in the future research work, the SBMLR algorithm is considered to be innovatively integrated with other algorithms in order to continuously improve the performance of the recognition algorithm.

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