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Utilizing Data Analytics to Dig Deeper into UFC Mixed Martial Arts Technical Moves and Provide a Reference for Teaching Martial Arts to College Students

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Abstract With the advancement of curriculum reform in colleges and universities, the teaching of wushu faces the problems of time and space limitation, solidified teaching mode and lack of resources. Meanwhile, as a traditional cultural treasure of the Chinese nation, wushu is of great significance to cultivate college students' moral character, willpower and self-protection ability. In this study, the characteristics of UFC mixed martial arts technical movements were deeply explored through data analysis techniques, which provided scientific references for college students' martial arts teaching. The study adopts the improved ST-GCN model fused with the spatio-temporal attention mechanism to recognize and analyze the wushu movements, extracts the skeleton joint points through the OpenPose posture estimation technique, and conducts an in-depth analysis of the changes in the center of gravity displacements of the wushu movements based on the Huanglongquan Puffing Wind Palm. The results show that: the accuracy of the improved I-ST-GCN model in recognizing the four movements of punching, side kicking, leg lifting, and squatting reaches 92.03%, which is better than that of the original ST-GCN model of 88.31%; the center of gravity change of Huanglongquan Piao Feng Palm is most significant in the third phase (force generation phase) among the three movement phases, with the value of the change of the center of gravity in the X-axis of 0.814 m; and the fusion of spatio-temporal attention of the Improved ST-GCN model reaches 90.44% in recognition accuracy, which is 6.3 percentage points higher than the traditional model. Based on the results of the study, this paper proposes implementation paths such as optimizing the teaching environment of martial arts, innovating teaching methods, constructing a teaching improvement mechanism and establishing an interactive learning community. The study shows that the data analysis technology can effectively mine the characteristics of wushu technical movements, provide new ideas for wushu teaching in colleges and universities through scientific analysis, and promote the deep integration of wushu education and modern technology.

Index Terms Data analysis, Mixed martial arts, Spatio-temporal graph convolutional network, Stance estimation, Action recognition, Wushu teaching in colleges and universities

I. Introduction

Under the background of the new era, the reform of college curriculum has become an important means to enhance and improve the school education, and to realize the reform of the curriculum in the process of development. Wushu has become one of the essential disciplines in the curriculum of colleges and universities, and the need for rectification has been gradually exposed in daily teaching, and at the same time, with the development of modernization of education, the teaching of wushu is limited by factors such as time, space and other factors, and the teaching mode of wushu classroom is solidified [1]-[3]. At the same time, there is a lack of teaching resources, unable to meet the students' personalized demand for knowledge of martial arts and other real problems, which has become the objective existence of the development of martial arts constraints at the present time [4], [5]. In the new era of the development of Internet technology, the exploration and development of new modes and new ideas for the teaching of wushu provide new development ideas for improving the teaching of wushu [6].

Wushu has a long history and deep cultural deposits, and is a treasure of the Chinese nation, with profound philosophies embedded in the techniques [7]. Wushu practitioners not only need to master certain wushu techniques and understand traditional Chinese wushu culture, but also need to have a high level of wushu moral cultivation, which is the goal of lifelong learning and pursuit of wushu practitioners, and is also the basic quality that wushu practitioners should have [8], [9]. Contemporary college students still have many problems in moral character, martial arts knowledge and ability, will quality, personal safety knowledge and self-protection ability [10]. The comprehensive ability training of wushu during the university can help improve the moral character of college students, inherit the traditional wushu culture, and exercise the will quality of perseverance [11], [12]. As well as mastering basic personal safety knowledge and self-protection ability, it plays an important role in cultivating and practicing socialist core values of education, and cultivates comprehensively developed socialist builders and successors for the country [13]-[15].

Curriculum reform in colleges and universities in the context of the new era has become an important means to enhance and improve school education, and to realize the reform and renewal of the curriculum in the process of development. Wushu has become one of the essential disciplines in the curriculum of colleges and universities, and the need for rectification has been gradually exposed in daily teaching, and at the same time, with the development of modernization of education, the teaching of wushu is limited by time, space and other factors, and the teaching mode of wushu classroom is solidified. At the same time, there is a lack of teaching resources, unable to meet the students' personalized demand for wushu knowledge and other real problems, which has become the objective existence of the development of wushu at present. In the new era of the development of Internet technology, the exploration and development of new modes and new ideas for improving the teaching of wushu provide new development ideas. Wushu has a long history and deep cultural deposits, is the treasure of the Chinese nation, and contains profound philosophy in the technology. Wushu practitioners not only need to master certain wushu techniques and understand traditional Chinese wushu culture, but also need to have a high level of wushu moral cultivation, which is the goal of lifelong learning and pursuit of wushu practitioners, and is also the basic quality that wushu practitioners should have. Contemporary college students still have many problems in moral character, knowledge and ability of martial arts, will quality, personal safety knowledge and self-protection ability. Cultivating the comprehensive ability of wushu during the university period can help to improve the moral quality of college students, inherit the traditional wushu culture, and exercise the will quality of perseverance. As well as mastering basic personal safety knowledge and self-protection ability, it plays an important role in cultivating and practicing socialist core values, and cultivates comprehensively developed socialist builders and successors for the country.

This study is carried out in two dimensions: the algorithm for recognizing the technical movements of wushu and the teaching application. First, wushu movements are recognized and analyzed by computer vision technology, the skeleton joint points are extracted by OpenPose posture estimation technology, and the improved spatio-temporal graph convolutional network (ST-GCN) fused with spatio-temporal attention mechanism is introduced to model and recognize the wushu movements. Then, an in-depth analysis is carried out based on the center of gravity displacement change of the Huanglongquan Drifting Wind Palm technical movement to explore the kinematic characteristics of the martial arts movement from the movement trajectories of the XYZ coordinate axes. Finally, based on the results of the technical analysis, the implementation path of wushu teaching mode in colleges and universities is proposed, including optimizing the teaching environment, innovating the teaching method, constructing the teaching improvement mechanism and establishing an interactive learning community, etc. The aim is to provide scientific reference for wushu teaching in colleges and universities by means of the data analysis technology, to promote the in-depth fusion of wushu education and modern technology, and to improve the effect of wushu learning for college students.

II. Improved ST-GCN Wushu action recognition model incorporating spatio-temporal attention

II. A. Machine learning based image preprocessing techniques

Due to the noise in the original image obtained by the acquisition system, direct feature extraction in the original image will reduce the accuracy of the later recognition algorithm to a certain extent, so in the pre-feature extraction needs to be de-noised images, this paper adopts a simpler operation of the wavelet transform method to remove the Gaussian noise contained in the image, and set up the noise-containing original image signal as follows:

$$y_i = f(t_i) + e_i \quad i = 1, 2, \cdots, n \tag{1}$$

Type, e_i said noise value, $f(t_i)$ said not contaminated original signal, want to achieve the elimination of noise will need to calculate an estimate of $\hat{f}(\cdot)$, So set $c_0 = y_i$ for the noise signals of the initial sequence, using orthogonal wavelet transform to c_0 multistage decomposition process is as follows:

$$c_{j+1} = D_e H c_j \tag{2}$$

$$d_{j+1} = D_e G c_j \tag{3}$$

where c_{j+1} is the approximation signal; d_{j+1} is the detail signal; G is the Gaussian filter; H is the low-pass filter; and D_e is the sampling operator. The approximation signal c_j and the estimates of the detail signals $d_1, d_2, \cdots, d_j$ are obtained after decomposition as follows:

$$\hat{d}_j = \begin{cases} \overline{d}_j, & 1 \le j \le j_0 \\ d_j, & j_0 < j \le J+1 \end{cases} \tag{4}$$

where j_0 denotes the truncation parameter of the low-resolution image, and the actual value of $\overline{d}_j$ can be derived from the wavelet threshold threshold. If Q denotes the threshold threshold, there are two cases of thresholding of d_j, hard thresholding and soft thresholding, and the hard thresholding is:

$$\overline{d}_j = \begin{cases} d_j, & |d_j| \ge Q \\ 0, & \text{other} \end{cases} \tag{5}$$

The soft-threshold treatment can be expressed as follows:

$$\overline{d}_j = \begin{cases} \operatorname{sgn}(d_j)(|d_j| - Q), & |d_j| \ge Q \\ 0, & \text{other} \end{cases} \tag{6}$$

The magnitude of the threshold threshold Q depends on the magnitude of the mean square deviation σ of the noise, which is estimated for σ using the first layer of detailed signal as follows:

$$\sigma = median(|d_1|) / 0.6745 \tag{7}$$

By reconstructing the approximation signal and the final processed detail signal, the estimated value of the noise signal can be obtained to complete the denoising of the image.

II. B. Human mixed martial arts technique movement recognition algorithm

II. B. 1) Video pose estimation

In this paper, we use the OpenPose pose estimation method [16], [17], which combines both speed and accuracy, to detect skeleton joint points from videos.OpenPose is a top-down, deep learning-based, real-time pose estimation method, which enables the extraction of joint points of the human face, torso, limbs, and hands, as well as maintains the speed advantage in multiplayer scenarios.

The OpenPose network adopts a multi-stage prediction approach, introducing the first 10 layers of the VGG-19 model as the base network, transforming the input image into feature F, and regressing $L(p)$ and $S(p)$ in stages through a multi-layer convolutional neural network (C), where: $L(p)$ is the affinity vector fields (PAFs), which describes the pointing of the joints in the skeleton; $S(p)$ denotes the confidence level of the joints, which describes the location information of the joints.

The prediction process predicts the affinity vector fields L' through the first T_P stage, and the confidence S' through the second T_C stage. At each stage the results of the previous stage are fused with the original features to preserve the lower and higher level features of the image. When $1 \le t \le T_p$, L' is calculated as:

$$L^1 = \phi^1(F), t = 1 \tag{8}$$

$$L' = \phi'(F, L^{t-1}), 2 \le t \le T_P \tag{9}$$

When $T_p \le t \le T_p + T_c$, S' is calculated as:

$$S^{T_p} = \phi'(F, L^{T_p}), t = T_P \tag{10}$$

$$S' = \phi'(F, L^{T_p}, S^{t-1}), T_P < t \le T_P + T_C \tag{11}$$

After predicting the position and affinity vectors of the joints, the Hungarian algorithm is used to perform bisection optimal matching of the neighboring joints, and finally the pose information belonging to the same human body is obtained.

II. B. 2) Data pre-processing

OpenPose balances speed and accuracy, but a certain intensity of node jitter occurs when applied to video. Therefore, assuming that the moving bits of the joints are approximately uniform over a short period of time, the coordinates of the missing points are computed in the time domain by combining the node information of the neighboring video frames.

In the time-domain mean filling method, suppose that there is a missing keypoint $P_j^i(x_j^i, y_j^i)$ in frame i, where j indicates the body joint number. The missing point is filled by calculating the mean of the keypoints within an interval of K frames. The calculation method for the missing point $P_j^i(x_j^i, y_j^i)$ is as follows:

$$\begin{cases} x_j^i = \dfrac{\sum_{k=1}^{K} x_j^{i-k} + x_j^{i+k}}{2K} \\ y_j^i = \dfrac{\sum_{k=1}^{K} y_j^{i-k} + y_j^{i+k}}{2K} \end{cases} \tag{12}$$

The experimental results on the non-missing joint points show that a better filling effect can be achieved when $K = 2$. Then the Holt exponential smoothing method is used to carry out the smoothing operation on the coordinates of the joint points to remove the extreme points in the original pose data to reduce the jitter, while further correcting the filled joint point coordinates, which is calculated by the formula:

$$S_i = \alpha x_i + (1-\alpha)(S_{i-1} + b_{i-1}) \tag{13}$$

$$b_i = \beta(S_i - S_{i-1}) + (1-\beta)b_{i-1} \tag{14}$$

where, α is the smoothing parameter and is usually set to 0.5; x_i, S_i, b_i are the joint coordinate detection value, smoothing value, and trend increment of the i th frame, respectively; S_i, b_i are initially set to be the smoothed value of the joint coordinates in frame 1, and the difference between the joint coordinates in frame 2 and frame 1, respectively.

II. B. 3) Motion Feature Extraction

A single video frame is able to acquire 18 2D skeletal joint points of the moving target i.e. 36 features, and to further reduce redundant features, salient features that can express human motion are extracted from them. First, remove the 4 keypoints related to the left and right eyes and ears that are irrelevant to the studied action. The retained keypoints are nose (x_1, y_1), neck (x_2, y_2), left shoulder (x_3, y_3), right shoulder (x_4, y_4), left elbow (x_5, y_5), right elbow (x_6, y_6), left hand (x_7, y_7), right hand (x_8, y_8), left hip (x_9, y_9), right hip (x_{10}, y_{10}), left knee (x_{11}, y_{11}), right knee (x_{12}, y_{12}), left foot (x_{13}, y_{13}), and right foot (x_{14}, y_{14}). The joint points of the human skeleton are the absolute coordinates under the Cartesian coordinate system are more sensitive to the changes of target distance, position and view angle, in this paper, 13 action vectors reflecting the limb activities are extracted from the 14 joint points based on the limb division by vector operation.

The action vector extraction method is shown in Fig. 1, where (a) and (b) represent the action vector extraction and Cartesian coordinate system, respectively. The calculation method is the difference between the coordinates of two neighboring joints in the same video frame, and the calculation formula is:

$$V_\alpha^i = (x_j^i, y_j^i) - (x_{j+z}^i, y_{j+z}^i), \alpha \in \{a, b, \cdots, m\} \tag{15}$$

Among them, $V_a, V_b, \cdots, V_m$ are the 13 extracted action vectors, each of which is a value of two coordinates (x, y) in the right-angled coordinate system, which characterizes the angle and magnitude information of the activity of each limb.

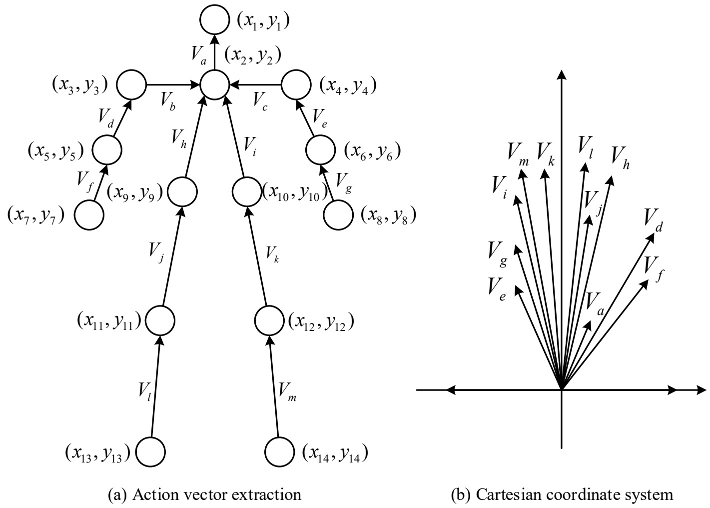

Figure 1: Schematic diagram of action vector extraction

The range of values of the skeleton joints is proportional to the video resolution. In order to standardize the scale size of different samples and reduce the differences between samples, the action vector $V(x, y)$ is processed as follows:

$$\begin{cases} \overline{x} = \dfrac{x}{v_w} \\ \overline{y} = \dfrac{y}{v_h} \end{cases} \tag{16}$$

where (v_w, v_h) is the resolution of the video source and $\overline{V}(\overline{x}, \overline{y})$ is the action vector normalized to [0, 1]. Since the duration of different video samples is inconsistent, the size of the time step is unified and set to T by complementing 0. The feature dimension of each time step is 25.

II. C.Improved ST-GCN model incorporating spatio-temporal attention

II. C. 1) Spatio-Temporal Graph Convolution ST-GCN

In Spatio-Temporal Graph Convolutional Network [18] (ST-GCN), the human skeleton map is captured by a pose estimation algorithm or kinectis camera and transformed into joint point coordinate information, which in turn constructs the corresponding connectivity relationships based on the skeletal data. The constructed human joint point map sequence data is inputted into the spatio-temporal graph convolution network ST-GCN, and graph convolution in both spatial and temporal dimensions is performed to extract more advanced feature maps Finally, the final results are outputted by classifying them through the fully connected layers, classifiers, and so on.

Translated in mathematical language, this can be expressed as inputting a sequence of human body joints (N, T), where N denotes the N joints of the human body and T denotes the length of the input sequence. An undirected graph $G = (V, E)$ is constructed on this basis, with V representing the set of graph nodes, i.e., $V = \{v_i \mid t = 1, 2, \cdots, T, i = 1, 2, \cdots, N\}$. The E represents the set of edges and consists of two parts, E_x and E_t, where E_x denotes the realistic connectivity of the human body's joints on the current frame, and E_t denotes the temporal connectivity of the same joints under different frames.

From the well defined undirected graph G in the above paragraph, the graph convolution operation is then defined under the current frame (at the spatial dimension level). For the node $V_{\tau i}$ on the τ frame, it can be represented as:

$$f_{out}(v_{\tau i}) = \sum_{v_{rj} \in s_i} \frac{1}{T_{ij}} f_{in}(v_{\tau i}) w(l_i(v_{\tau i})) \tag{17}$$

where, v represents the node, f_{in} represents the feature mapping, s_i is the sampling region for the convolution of the target node $v_{\tau i}$, the weight function w is used to provide the weight vector, and the mapping function l

assigns weights to the feature vectors. The size of s_i varies in the number of subsets it contains. 0 denotes the center of gravity of the skeleton, and s_i consists of three subsets: s_{i1} is the target node itself, s_{i2} is the centripetal node set, and s_{i3} is the centrifugal node set. Each subset has its own label and mapping l_i, and T_{ij} denotes the cardinality of the subset s_i in which the vertex $v_{\tau j}$ is located. Converting the formulae yields a graph convolution realized in the spatial dimension as:

$$f_{out} = \sum_{k}^{K_v} w_v (f_{in} (\tilde{A}_k \odot M_k)) \tag{18}$$

where K_v denotes the size of the convolution kernel, $\tilde{A}$ is the normalized form of the adjacency matrix A, M is a learnable weight matrix, and the $\odot$ symbols denote dot products.

Next, we define the graph convolution on adjacent frames. For each vertex v_i, we center on it and look at the previous frame and the next frame. Its corresponding same key points are only those two, which means that in the entire sequence of human body key points, from a temporal perspective, each human body key point has two fixed neighboring nodes. Therefore, we only need to perform a 2D convolution on the feature map output by the model to complete the graph convolution operation in the temporal dimension.

II. C. 2) Improved ST-GCN design incorporating spatio-temporal attention

(1) ST-GCN structure with fused spatio-temporal attention

In this paper, on the basis of the original model ST-GCN module, the spatio-temporal attention module is added to extract the human joint point features from both the temporal and spatial dimensions and fused, which strengthens the global feature information of the feature map. The improved ST-GCN model incorporating the spatio-temporal attention mechanism contains 10 basic units with a starting channel number of 3. The skeleton information of human joints extracted by the OpenPose algorithm will first pass through the BN layer before inputting into the basic units to do the normalization process in order to enhance the data normality.

(2) Improved ST-GCN basic unit with fused spatio-temporal attention

Each basic unit of the ST-GCN model with fused spatio-temporal attention consists of a spatio-temporal attention module, a spatial GCN map convolutional layer, and a temporal TCN convolutional layer. The data first passes through the spatio-temporal attention module, and then enters the spatial graph convolution module and the temporal graph convolution module to extract the human joint point skeleton feature information after adding temporal attention and spatial attention in spatial and temporal dimensions, respectively.

The specific computation process is as follows: the attention weight W_t is computed in the time dimension, σ denotes the sigmoid activation function, and Conv2d stands for the convolution operation, with a convolution kernel size of (1, 3) and a padding padding of (0, 1):

$$W_t = \sigma(Conv2d(x)) \tag{19}$$

The input x is then subjected to a weighting operation in the time dimension, with · representing the multiplication:

$$x' = x \cdot W_t \tag{20}$$

Similarly, the attentional weight W_s is computed in the spatial dimension, viz:

$$W_s = \sigma(Conv2d(x')) \tag{21}$$

The input x is then subjected to a weighting operation on the spatial dimension:

$$x'' = x' \cdot W_s \tag{22}$$

The input feature x'' after the above processing then contains features in both temporal and spatial dimensions.

III. Recognition effects of martial arts movements and implementation paths for teaching martial arts

III. A. Analysis of the effect of martial arts movement recognition

III. A. 1) Experimental Data and Assessment Methods

(1) Experimental data

In this paper, four common martial arts movements, namely punching, side kicking, leg lifting, and squatting, are selected for recognition, and the dataset consists of part of the Le2i dataset and videos collected online. The length of the intercepted videos is between 5 seconds and 10 seconds, with a total of 155 video numbers, including 57 punches, 32 side kicks, 39 leg lifts, and 27 squats. 1000 images were selected in the human target detection task and divided into training, validation and test sets according to 8:1:1. The training set and test set are divided according to 9:1 in the action recognition task, and the number of pictures in the training set and test set are counted as 15341 and 1694 after the video is truncated.

(2) Evaluation metrics

The model uses Precision (P), Recall (R), Weighted Score (F1), Average Precision (AP), Mean Average Precision (mAP), Accuracy (A), and Frames per Second (FPS) as the evaluation metrics to examine the model performance.

III. A. 2) Experimental Comparison of Human Detection and Improved ST-GCN Modeling

In order to validate the improvement on the target detection model for pose estimation, three algorithms, traditional video pose estimation model (TVAEM), ST-GCN model (ST-GCN), and improved ST-GCN model (I-ST-GCN), are used for comparative validation on the self-constructed dataset.The training process of the YOLOv5s_CBAM_DWConv target detection model is performed using the Adam optimizer with momentum of 0.9528, a total of 150 Epochs are trained, 45 Epochs are trained in the freezing phase, batch_size is set to 7, and the learning rate is 0.001, and after thawing, another 120 Epochs are trained, batch_size is set to 5, and the learning rate is 0.0001.

After obtaining the optimal model, it is combined with the pose estimation module in the TVAEM model and tested on the test set, and the comparison results of the performance metrics of the three algorithms are shown in Table 1. It can be seen that compared with the original model, the optimized model has a stable mAP value and improves the running frame rate.

Table 1: Performance index comparison results of three algorithms

Model	mAP(%)	FPS	Pixel value
TVAEM	73.35	21	340×250
ST-GCN	84.01	33	340×250
I-ST-GCN	85.29	32	340×250

III. A. 3) Action Recognition Effect Analysis

The videos in the action recognition dataset are acquired by the method of this paper and TVAEM to obtain the human skeleton data in each frame, and the skeleton data of each video sample is stored as a file in json format, which contains the skeleton information corresponding to the video frames and the action labels. The I-ST-GCN model is trained using this data, setting the number of rounds epoch to 150, the batch size batch_size to 30, and the learning rate to 0.001. The recognition effect of the model-trained actions is shown in Fig. 2. With the increase of the number of training rounds, the loss function gradually decreases, and the precision, recall and accuracy rates gradually increase and stabilize.

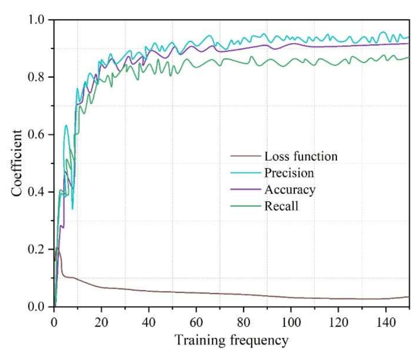

Figure 2: The identification effect of the model training action

After obtaining the optimal model, it was tested on the test set, and the results of the evaluation metrics for different actions are shown in Table 2, which shows that the algorithm achieves an accuracy of 92.03% and an FPS of 21.35 for the recognition of the four actions: punching, side kicking, leg lifting, and squatting.

Table 2: Evaluation of different actions

Action	P(%)	R(%)	F1(%)	A(%)
Punch	86.66	85.36	86.87	89.67
Side kick	94.69	91.14	91.57	93.85
Lifting leg	90.96	88.84	89.14	91.15
Squat down	92.03	87.03	92.06	93.45
Mean value	91.09	88.09	89.91	92.03

The results of the evaluation indexes of different algorithms are shown in Table 3. It can be seen that optimizing the target detection structure of TVAEM and adding a new spatio-temporal attention module improve the effectiveness of the original algorithm for martial arts movement recognition to a certain extent.

Table 3: Evaluation of different algorithms

Model	P(%)	R(%)	F1(%)	A(%)
TVAEM	84.14	81.51	82.44	88.04
ST-GCN	88.21	85.48	87.37	88.31
I-ST-GCN	90.44	88.45	89.64	92.03

III. B. Analysis of changes in center of gravity displacement of martial arts technical movements

Huanglongquan is a unique type of technical boxing in traditional martial arts, and Piao Feng Palm is a typical movement in Huanglongquan, Piao Feng Palm, also known as cutting palm, chopping palm, is a kind of chopping technique with the side of palm root. In this paper, the Y axis is used as the vertical axis of the human body to calculate the displacement change of the center of gravity in the XYZ coordinate system, and the XZ coordinate system is used to calculate the displacement change of the center of gravity from the other two dimensions, so that through kinematic analysis we can reveal the displacement change of the center of gravity of the body in the process of movement. By interpreting the changes between the three phases and their possible correlations from different dimensions (i.e., XYZ coordinate system), the kinematic changes of the Puffing Wind Palm are described from the three-dimensional x/y/z coordinate system (axes).

Table 4 shows the results of the stage division of the floating wind palm. By dividing the floating wind palm into three phases, the kinematic data extracted from the three-dimensional analysis system are used to describe the changes of the center of gravity displacement of the floating wind palm technical movement in three-dimensional space.

Table 4: The division of the Piaofeng palm

Stage division	Time/s	Describe
First stage	0.738—0.994	By microspinning to increase accumulation
Second order	0.455—0.718	Lift up your arm
Third stage	0.152—0.404	Follow the ready posture

III. B. 1) Trajectory analysis of the center of gravity in the X-axis coordinate system

Figure 3 is the change curve of the starting position of the center of gravity in the X-axis, Figure 4 is the change curve of the displacement of the center of gravity of the human body in the X-axis, and Figure 5 is the change curve of the velocity of the center of gravity in the X-axis. By dividing the sections of Huanglongquan Puffing Wind Palm technical movement, combined with video images and 3D data, the Puffing Wind Palm technical movement is divided into three phases to analyze the feasibility:

Staging phase: the starting position change of the practitioner does not have a large rise and fall during the whole staging process, and the displacement value shows a maximum value of 0.814 meters during the staging phase, which indicates the maximum body deflection at the beginning of the movement. The speed of movement in the accumulation part of the movement was not large, but the zero point of the movement was 0.0061 m/S, which shows that the practitioner's starting position change was relatively smooth during the accumulation process.

Upper lead phase: the displacement value in this phase is decreasing in a parabolic trend, and a decrease in the displacement value indicates that the center of gravity of the body is shifting forward. Velocity changes are increasing in a straight line, which also indicates that this phase is preparing for the final phase. It can be observed that the center of gravity of the body can be maintained at a relatively stable level despite the increase in speed and the forward shift of the body, which indicates the degree of mastery of the technique by the practitioner.

Power Stage: In this stage, there is a clear tendency for the center of gravity to press down from back to front, and in the final rise and fall, it can be analyzed that as the speed increases, the displacement value of the practitioner becomes smaller. This reflects that the performer has increased the speed of the movement while keeping the center of gravity stable.

To summarize, the more obvious change of the X-axis center of gravity during the whole movement is in the third stage, which shows that the Puffing Wind Palm will affect the change of the body's center of gravity accordingly in the process of power conversion.

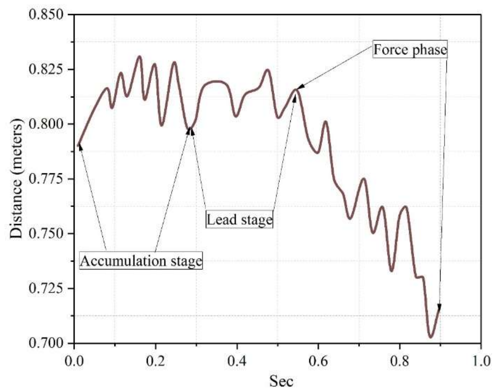

Figure 3: The initial position of the center of gravity in the X-axis

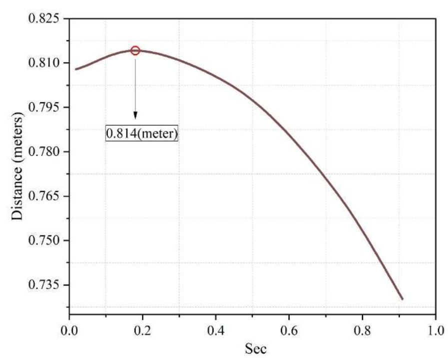

Figure 4: The displacement curve of the center of gravity in the X-axis

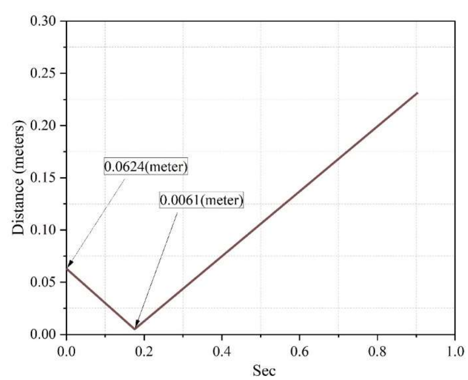

Figure 5: The velocity of the center of gravity in the X-axis

III. B. 2) Trajectory analysis of the center of gravity in the Y-axis coordinate system

Figures 6 to 8 show the variation curves of the center of gravity in the Y-axis starting position, displacement and velocity, respectively. The maximum value of the center of gravity in the Y-axis dimension in the accumulation phase is 0.6849 m and the minimum value is 0.6523 m. The change of the center of gravity of the body in the Y-axis dimension during the movement is the basic condition to maintain the stability of the body, and when there is a large center of gravity shift of the body, the proprioception and the nervous system instinctively keep the body in a more balanced range of values.

The nodes in the force generation phase have greater ups and downs, indicating that the body's center of gravity fluctuates more in the Y-axis dimension during this phase of the movement, and the greatest displacement of the body's center of gravity also occurs in the final force generation phase, where the maximum value of the center of gravity shift is 0.6931 meters and the minimum value is 0.6426 meters. The possible reason for this is due to the fact that the rotation of the feet in the final power generation phase generates force transfer, which then forms a power chain on one side of the body, at which time the body needs to rotate from the right side to the left side to achieve a power generation torsion, which is the reason for the large change in the center of gravity of the body.

The possible reasons for the gradual decrease in displacement change from right to left in a linear fashion, from the starting value of 0.6781 meters to 0.6429 meters, may be related to the change in the center of gravity of the body and the size of the body joint angle produced. The change in the center of gravity of the body prompted an increase in speed from the initial value of 0.0376 m/s to 0.0445 m/s, which was slowly increasing at a linear frequency.

The change in the center of gravity of the Y-axis during the whole movement process is more obvious in the third stage, which indicates that the Puffing Wind Palm will affect the change in the center of gravity of the body in the process of power conversion. The displacement and speed reflect that the closer the point of mass is to the end point, the faster the speed of the movement, which is related to the force characteristics of the movement.

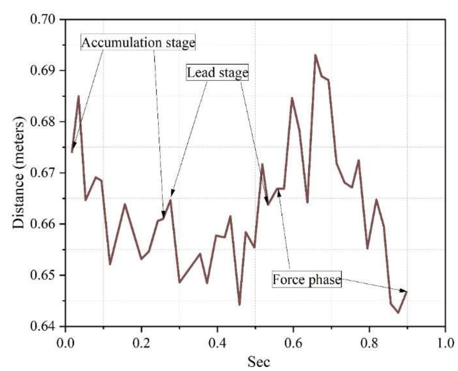

Figure 6: The initial position of the center of gravity in the y axis

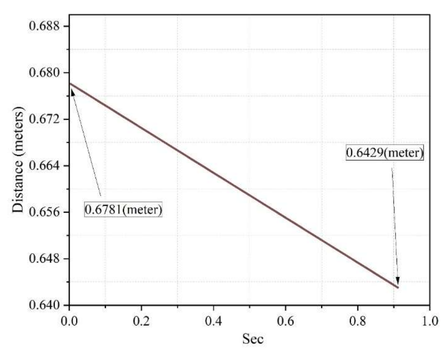

Figure 7: The displacement curve of the center of gravity in the Y-axis

III. B. 3) Trajectory analysis of the center of gravity in the Z-axis coordinate system

Figure 9 shows the overall trend of the displacement of the body's center of gravity in the Z-axis dimension during the rehearsal of the floating wind palm maneuver. The displacement of the center of gravity of the body in the Z-axis dimension changes during the accumulation phase, with a maximum value of 1.209 meters and a minimum value of 1.136 meters. The magnitude of the displacement of the body center of gravity reflects the degree of stability of the body of the performer during the whole movement process, and the lower the center of gravity, the better the stability of the movement. Combining the three phases and the range of activity of the body center of gravity displacement throughout the movement trajectory shows that the range of body center of gravity floating throughout the movement trajectory is not large.

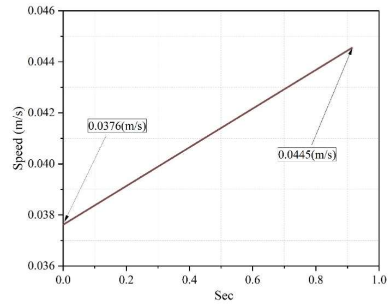

Figure 8: The velocity of the center of gravity in the y axis

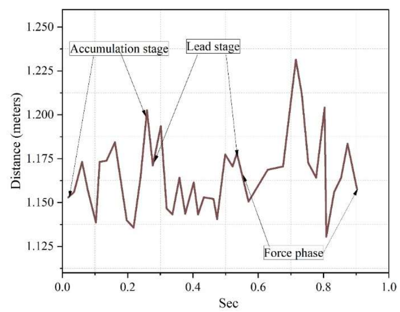

Figure 9: The initial position of the center of gravity in the z axis

Figure 10 shows the results of the displacement change of the center of gravity of the human body in the Z-axis dimension. The displacement value from the beginning of the 1.1582 meters in a parabolic trend is rising, when the displacement value reaches the maximum value in the whole trajectory, there is gradually a trend of falling back, when the displacement value falls back to 1.1648 meters when the movement is over.

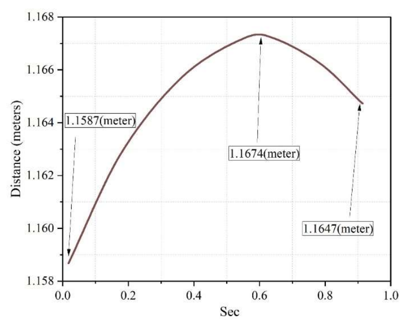

Figure 10: The displacement curve of the center of gravity in the z axis

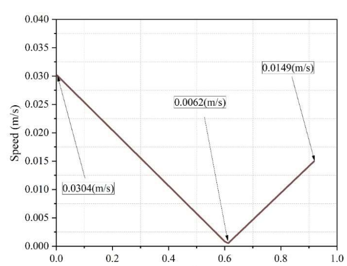

Figure 11: The velocity of the center of gravity in the z axis

Figure 11 shows the results of the velocity variation of the center of gravity in the Z-axis. At the very beginning of the Z-axis the velocity reaches a peak value of 0.0315 meters per second, and then gradually decreases, and at -0.4 seconds the velocity appears to be a minimum value of 0.0001 meters per second throughout the movement, and when it reaches the minimum value of the velocity gradually increases linearly to 0.0165 meters per second, and at this point the movement ends. In summary, the change in the center of gravity of the Z-axis is 0.108 meters. The more obvious change of the center of gravity of the Z-axis during the whole movement is in the third stage. This indicates that the Puffing Wind Palm will have a corresponding effect on the change of the center of gravity of the body during the process of force conversion.

III. C. Path of implementation of martial arts teaching model in higher education institutions

III. C. 1) Optimization of the Martial Arts Teaching Environment

The use of advanced technology can not only optimize the martial arts teaching environment, but also greatly enhance the students' martial arts learning experience. The application of artificial intelligence and data analysis technology can monitor students' martial arts learning performance in real time, provide them with rich martial arts learning resources, and students can learn high-quality martial arts teaching content anytime and anywhere through modern technology, as well as discuss with teachers and classmates online to form a virtual learning community.

III. C. 2) Innovations in martial arts teaching methods

Collect and analyze a large amount of data related to students' martial arts learning to develop more scientific and effective martial arts teaching methods. Scientific data analysis relies on the collection of students' learning behaviors, performance progress, and feedback information, and the ability to quickly process these complex data to reveal key influencing factors in the wushu learning process through pattern recognition and predictive analysis. Based on the results of data analysis, teachers can adjust their martial arts teaching methods.

III. C. 3) Construction of teaching improvement mechanisms

By monitoring and analyzing students' learning performance in real time to provide immediate feedback to students and teachers, an effective improvement mechanism for teaching Wushu can be established. When students are practicing Wushu movements, through motion capture technology and video analysis, the system is able to identify the accuracy of students' movements in real time and point out deficiencies. Immediacy feedback also includes real-time updates on learning progress and grades, enabling students to keep track of their learning status and adjust their Wushu learning style. The use of instantaneous feedback response also promotes interaction between teachers and students, enhances the efficiency of communication between teachers and students, and increases the fun of learning martial arts.

III. C. 4) Establishment of interactive learning communities

Establishing an interactive learning community can provide a platform for students to share their experiences, stimulate their interest in learning, and create a supportive and collaborative martial arts learning environment. Interactive learning communities can be established through modern technology such as online forums, social media groups and video conferencing platforms, where students can post their problems encountered in the process of Wushu learning, share their learning experiences or upload practice videos for feedback. Teachers can provide professional guidance in the interactive learning community and adjust their teaching programs based on students' discussions and feedback.

IV. Conclusion

In this study, we analyzed the recognition of UFC mixed martial arts technical movements through the improved ST-GCN model, explored the kinematic characteristics of martial arts movements, and proposed an implementation path for teaching martial arts in colleges and universities. The results show that the improved ST-GCN model incorporating spatio-temporal attention outperforms the traditional method in terms of recognition precision (90.44%), recall (88.45%), and accuracy (92.03%), and is able to effectively recognize common wushu movements such as punching, side kicking, leg lifting, and squatting. Through the analysis of the center of gravity displacement of the Huanglong Quan Piao Feng Palm technical movements, it was found that the value of the center of gravity change on the Z-axis was 0.108 m, and the maximum value of the center of gravity deviation on the Y-axis dimension amounted to 0.6931 m, and the center of gravity change was most significant in the third stage (power generation stage), which indicated that the Piao Feng Palm would have a significant impact on the change of the center of gravity of the body in the course of carrying out the transformation of the power. Based on the results of the study, implementation paths such as optimizing the teaching environment of wushu, innovating teaching methods, constructing a teaching improvement mechanism and establishing an interactive learning community were proposed. The application of data analysis technology in wushu movement recognition can provide teachers with a scientific basis for real-time guidance and correction of students' practice postures, thus improving the quality and effect of wushu teaching. At the same time, the establishment of interactive learning communities can stimulate students' interest in learning and create a supportive and cooperative wushu learning environment. To summarize, the application of data analysis technology in wushu teaching is of great value, which can promote the deep integration of wushu education and modern technology, and provide new ideas and methods for wushu teaching in colleges and universities.

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