Article

Motion Classification and Features Recognition of a Traditional Chinese Sport (Baduanjin) Using Sampled-Based Methods

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Abstract: This study recognized the motions and assessed the motion accuracy of a traditional Chinese sport (Baduanjin), using the data from the inertial sensor measurement system (IMU) and sampled-based methods. Fifty-three participants were recruited in two batches to participate in the study. Motion data of participants practicing Baduanjin were captured by IMU. By extracting features from motion data and benchmarking with the teacher's assessment of motion accuracy, this study verifies the effectiveness of assessment on different classifiers for motion accuracy of Baduanjin. Moreover, based on the extracted features, the effectiveness of Baduanjin motion recognition on different classifiers was verified. The *k*-Nearest Neighbor (*k*-NN), as a classifier, has advantages in accuracy (more than 85%) and a short average processing time (0.008 s) during assessment. In terms of recognizing motions, the classifier One-dimensional Convolutional Neural Network (1D-CNN) has the highest accuracy among all verified classifiers (99.74%). The results show, using the extracted features of the motion data captured by IMU, that selecting an appropriate classifier can effectively recognize the motions and, hence, assess the motion accuracy of Baduanjin.

Keywords: motion analysis; motion accuracy; inertial sensor measurement systems; Baduanjin

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1. Introduction

Baduanjin is a popular traditional sport in China that consists of eight motions [1]. It is a compulsory sports item of physical education (PE) in Chinese universities and a traditional sports item supported by the government [2]. However, the teaching and learning resources are relatively inadequate. For example, although 76.7% of Chinese universities taught martial arts in their PE curriculum, the high student-teacher ratio has adversely affected the teaching and learning of Baduanjin [3]. Because there are many students in the Baduanjin course, the teacher cannot observe the motions of each student and correct the errors immediately. As a result, the students are unaware of their inaccurate motions. Students repeat the same errors continuously, which finally have achieved dynamic setting of errors in motions [4,5].

In recent years, motion capture (MoCap) has been applied in sports to monitor the motions of learners in real time. Researchers developed the system for specific sports items, using the motion data obtained by MoCap [6,7]. The system is able to check the motions and give the information of the errors in the motions in real time to the exercisers to assist them in detecting and correcting their inaccurate motions. For example, Chen et al. [8] developed a system for assessing the motion quality of Tai Chi based on Kinect. The system uses Kinect to obtain the 3D data of motions of exercisers. The difference between the data from the exerciser and experts is calculated through dynamic time-warping (DTW) to assess the motion quality of the exerciser. Researchers applied this system to teach Tai Chi in universities and found that the system accelerates learning in Tai Chi novices.

The application of MoCap in PE can be divided into four categories based on its technical characteristics: optoelectric system (OMS) [9], electromagnetic system (EMS), image processing system (IMS) and IMU [10]. The disadvantages of OMS are its high cost and the issue with markers being obscured, which limits its practical application in PE [11,12]. EMS does not have an issue in obscuring markers, but it is prone to interference from the electromagnetic environment [13]. The advantage of IMS is that it is more accurate than EMS, and the measurement range is more comprehensive than that of OMS [10]. However, IMS has the problem of occlusion [10]. For example, in teaching, teachers may hide the optical sensor and cause the inability to effectively capture the motions of students, which has limited high-performance IMS application in PE. IMU does not have the disadvantage of occlusion compared to IMS technology [14]. Commercial IMUs (MVN Awinda system, Xsens, Enschede, Netherlands) have already been validated with motion accuracy. Moreover, IMU is the most mobile of the four categories of MoCap, making it a preferred application in PE [10,15]. It is undeniable that IMU has the problem of magnetic distortion, because it includes magnetometers [10]. For example, a MoCap glove for fingers (Smartglove developed by Rokoko) applied the sensors, which exclude magnetometers to avoid magnetic distortion [16]. However, the motions of Baduanjin are the overall human body motions, which do not require capturing the motions of fingers. The magnetic distortion of IMU can be ignored.

Therefore, we propose developing a system using IMU to capture the motions of Baduanjin to assess the motion accuracy of students and assist teachers and students in identifying errors in the motions of Baduanjin. The system needs to recognize and assess the motions of Baduanjin effectively. The purpose for developing recognizing motions of Baduanjin is that Baduanjin has a complete set of motions. The reason is that the sequence of motions in Baduanjin is fixed (from Motion-1 to Motion-8), which means the sequence of motions cannot be adjusted at will. The sequence of motions must be followed. However, in the actual teaching and learning environment, the students are unable to perform Baduanjin with the correct sequence of motions. Therefore, the assessment system should be able to identify the motions to ascertain whether the student has followed the correct motion sequence. Recognizing motion and assessing motion accuracy can be solved as a classification issue. Commonly used classification methods can be divided into sample-based methods and sequence-based methods [17]. The sample-based methods mainly use classifiers, including k -NN, SVM, Naive Bayes (NB), Logistic Regression, Decision Tree (DT), Artificial Neural Network (ANN) and CNN. The sequence-based methods mainly include DTW, Hidden Markov Model (HMM) and Recurrent Neural Network (RNN). In this study, the effectiveness of the sample-based methods, namely (even mainly classifiers) k -NN, SVM, NB, Logistic Regression, DT, ANN (including two commonly ANN classifiers) and 1D-CNN, was tested.

2. Materials and Methods

2.1. Overview

This study consists of three steps, namely capturing motion data of Baduanjin on IMU, extracting features and reducing feature dimensionality, and assessing and recognizing the motions of Baduanjin. Students from a university in Southwest China were invited to participate in the study. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the University of Malaya Research Ethics Committee (UM.TNC2/UMREC-558).

First, the motion data of all participants were captured when they practiced Baduanjin, using IMU. Second, the features were extracted from the motion data. The raw data needed to be converted into quaternion format for data analysis. Usually, the extracted features of motion data in practical applications have high dimensionality. Thus, dimensionality reduction is required to prevent data redundancy. The last step is to verify the effectiveness of the motion assessing and recognition of Baduanjin on sample-based methods. In sample-based methods, motions are assigned labels, regardless of the previous motion classification.

These classification methods use the extracted relevant features from the motion data for training the classifier based on labels. After the model parameters of the classifier are trained, unlabeled motions can be classified. Therefore, accessing motion accuracy of Baduanjin has been converted into a classification problem. Experts of Baduanjin were invited to grade the accuracy of the captured motions and then use the assessment result as a label to train the eight classifiers (see Figure 1).

2.2. Capturing Motion Data of Baduanjin, Using IMU

Undergraduate students with no clinical/mental illness or physical disability from a university in Southwest China were invited to participate in this study. Participants read the information sheet that outlined the purpose and procedure of the study. Those who agreed to participate in the study were given the consent form to sign.

The IMU used to capture the motion data of Baduanjin was Perception Neuron 2.0, which was developed by Noitom [14]. Perception Neuron 2.0 is a commercial IMU with 17 inertial sense units, and each unit comprises a 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer. The output of the captured motion data is in a Biovision Hierarchy (BVH) motion file through the Axis Neuron software developed by Noitom. The effectiveness of Perception Neuron 2.0 in measuring motion accuracy has been experimentally confirmed by Sers et al. [18].

Before measuring the motion data, participants were required to practice Baduanjin for 30 min to familiarize themselves with the motions and warm up their body. After the practice, the motion data of participants immediately were captured by IMU when they practiced Baduanjin. No feedback was given to participants during practice and the capturing of the motions. The eight standard motions of Baduanjin are shown in Figure 2.

2.3. Extracting Features of Motion Data

2.3.1. Extracting and Converting Raw Data

The output format of the motion data is the BVH file, which is a format used to store skeleton hierarchy information and three-dimensional motion data [19]. Perception Neuron 2.0 uses 17 sensors to measure the motion data of 17 points of the body. The BVH skeleton hierarchy information and skeleton model are shown in Figure 3.

The format of the skeleton motion data is recorded in the BVH file with the rotation data represented by Euler angles. Rotation data expressed by Euler angles have gimbal locking and singularity problems. Therefore, the Euler angle data were converted into quaternions to avoid such problems in this study [20]. Four-tuple notation was used to represent quaternion as follows:

$$q = [w, x, y, z] \quad (1)$$

In Equation (1), w is the scalar component, and x , y and z are the vectors.

If the order of rotation in Euler angle is z , y , and x , and set we α , β , and γ to represent the rotation angles of the object around x , y , and z axes, the corresponding quaternion can be converted as follows:

$$\begin{aligned} q &= \begin{bmatrix} w \\ x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \cos(g/2) \\ 0 \\ 0 \\ \sin(g/2) \end{bmatrix} \begin{bmatrix} \cos(b/2) \\ 0 \\ \sin(b/2) \\ 0 \end{bmatrix} \begin{bmatrix} \cos(a/2) \\ \sin(a/2) \\ 0 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} \cos(g/2) \cos(b/2) \cos(a/2) + \sin(g/2) \sin(b/2) \sin(a/2) \\ \cos(g/2) \cos(b/2) \sin(a/2) - \sin(g/2) \sin(b/2) \cos(a/2) \\ \cos(g/2) \sin(b/2) \cos(a/2) + \sin(g/2) \cos(b/2) \sin(a/2) \\ \sin(g/2) \cos(b/2) \sin(a/2) - \cos(g/2) \sin(b/2) \sin(a/2) \end{bmatrix} \end{aligned} \quad (2)$$

After converting the raw data into quaternions, the quaternions were converted into unit quaternions to facilitate extracting features.

Figure 1. Flow diagrams of the study.

Motion 1: Holding the Hands High with Palms Up to Regulate the Internal Organ

Motion 2: Posing as an Archer Shooting Both Left- and Right-Handed

Motion 3: Holding One Arm Aloft to Regulate the Functions of the Spleen and Stomach

Motion 4: Looking Backwards to Prevent Sickness and Strain

Motion 5: Swinging the Head and Lowering the Body to Relieve Stress

Motion 6: Moving the Hands down the Back and Legs, and Touching the Feet to Strengthen the Kidneys

Motion 7: Thrusting the Fists and Making the Eyes Glare to Enhance Strength

Motion 8: Raising and Lowering the Heels to Cure Diseases

Figure 2. Eight standard motions of Baduanjin.

Figure 3. The skeleton model of BVH file for Perception Neuron 2.0.

2.3.2. Extracting Features

After extracting and converting raw data to unit quaternions, the features were extracted from the data to represent each type of motion in the form of feature vectors. The extracted features used in motion recognition include features of time-domain, frequency-domain and wavelet. The time-domain features include the mean, variance, standard deviation, skewness, kurtosis, quartiles, average absolute deviation and correlation coefficient between axes [21–23]. Frequency-domain features include the peak value, energy of the discrete Fourier transform spectrogram and discrete cosine transform [24,25]. Wavelet features include approximate wavelet coefficients and wavelet detail coefficients obtained after discrete wavelet transform [26]. In this study, we extracted the time-domain features of motion data.

1. Extracting time-domain features

After raw data were converted into the unit quaternion of 17 skeleton points, the scalar component was removed, leaving the three vectors of [w, x, y, z]. For each skeleton point, the features are represented as an $n \times 1$ dimensional vectors: $X = [X_1, X_2, \dots, X_n]^T$. The mean, variance, standard deviation, skewness, kurtosis and quartile deviation of the time-domain features were extracted. The description of the features is shown in Table 1.

Table 1. The extracted features in this study.

Type of Feature	Feature ID	The Description of the Features
Time-domain features	1–3	The mean value of the three vectors of x, y, z
	4–6	The variance value of the three vectors of x, y, z
	7–9	The standard deviation value of the three vectors of x, y, z
	10–12	The skewness value of the three vectors of x, y, z
	13–15	The kurtosis value of the three vectors of x, y, z
	16–18	The quartile deviation value of the three vectors of x, y, z

The calculation equations for these features are as follows:

Mean:

$$m = \frac{1}{n} \sum_{i=1}^n X_i \quad (3)$$

Variance:

$$s^2 = \frac{1}{n} \sum_{i=1}^n (X_i - m)^2 \quad (4)$$

Standard deviation:

$$s = \sqrt{s^2} \quad (5)$$

Skewness:

$$S_k = \frac{\frac{1}{n} \sum_{i=1}^n (X_i - m)^3}{\left[\frac{1}{n} \sum_{i=1}^n (X_i - m)^2 \right]^{3/2}} \quad (6)$$

Kurtosis:

$$K = \frac{\frac{1}{n} \sum_{i=1}^n (X_i - m)^4}{\left[\frac{1}{n} \sum_{i=1}^n (X_i - m)^2 \right]^2} \quad (7)$$

Quartile deviation:

$$Q = Q_3 - Q_1 \quad (8)$$

In Equation (8), Q_1 represents the first quartile value, indicating that 25% of the value of vectors is less than or equal to Q_1 . Q_3 represents the third quartile value, indicating that 75% of the value of vectors is less than or equal to Q_3 .

2. Normalization

Normalization refers to transforming a dimensional expression into a scalar expression, which simplifies the calculations. In this study, the features were normalized to facilitate subsequent data analysis and improve the convergence speed of the classifier. The characters were normalized in the range of [0, 1], using the following equation:

$$x_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (9)$$

In Equation (9), x_i is the i -th data after normalizing. X_i is the i -th data in the feature vector before normalizing, while $X_{\max}$ and $X_{\min}$, respectively, are the maximum and minimum values in the feature vector.

3. Dimensionality reduction of feature vectors

High dimensionality of the feature vectors during training would result in the classifiers encountering problems such as large calculation load, data redundancy and poor visibility. In order to prevent these problems, it is recommended that dimensionality reduction be performed [27,28]. Dimensionality-reduction methods commonly applied in research include principal component analysis (PCA), linear discriminant analysis (LDA)

and independent component analysis (ICA) [27]. In this study, PCA was used to reduce the dimensionality of the features.

PCA is used for dimensionality reduction to calculate the covariance matrix and its eigenvalues and arrange them according to the size of the eigenvalues [28,29]. By setting the cumulative variance contribution rate threshold, the eigenvectors corresponding to a small number of eigenvalues are selected, and the projection matrix is formed. Finally, the original high-dimensional data can be projected to the low-dimensional space. This method has been widely used in motion recognition. Altun et al. [22] used IMU to recognize 19 actions in daily life, and the dimension of the extracted feature vector was as high as 1170. They used PCA to reduce the dimension to 30 dimensions from 1170.

The steps of dimensional reduction on PCA are as follows:

- Let the original data be the n -dimensional data of m ;
- Form the original data into matrix X with n -rows and m -columns;
- Zero-average each row of matrix X , that is, subtract the average value of this row;
- Calculate the covariance matrix;
- Calculate the eigenvalues of the covariance matrix and the corresponding eigenvector r .

Sort the eigenvectors row-by-row, from top to bottom, according to the corresponding eigenvalues, into a matrix, and take the first k rows to form a matrix P . The matrix P is the data after dimension reduction to k dimension.

2.4. Assessing Motion Accuracy of Baduanjin

Motion accuracy can be evaluated by assessing the difference between the test motions and the standard motions, and/or the difference or similarity between motions of students and teacher. After obtaining the differences or similarities between the motions, the motion accuracy of students can be scored by ratio mapping, such as the method adopted by X. M. Chen et al. [8]. However, the problem with this method is that the prerequisite stated that student achievements have to meet the normal distribution condition. It is not easy to guarantee that the condition is met in actual teaching. Therefore, two teachers were invited to score the levels of students' motions, and the assessment of motion accuracy was converted to a classification problem under the same type of motion.

2.4.1. Classifiers

1. k -NN

In k -NN, the k -Nearest Neighbors of the vector x in the training set are considered [22]. From k (preset) samples with the smallest distance, the category with the largest number of the same label was selected, and the test vector was classified into this category. In k -NN, the distance is generally applied Euclidean distance, and k is the preset value. However, there is no rule for the preset k value. In studies, the preset k value is that an appropriate value is related to the actual study situation [30]. Function `fitcknn` (Statistics and Machine Learning Toolbox) for k -NN was used in the MATLAB environment in this study [31].

2. SVM

SVM is a common classifier in motion recognition [32,33]. SVM constructs an N -dimensional hyperplane that optimally separates the dataset into categories on the theory of structural risk minimization [34]. It has significant advantages in classifying small samples and high-dimensional data [35]. In this study, SVM was applied to different feature vectors that belonged to more than two classes (8 classes). Following the one-versus-the-rest method, n different binary classifiers were trained, where each classifier recognizes one of n motion types. Function `fitcecoc` (Statistics and Machine Learning Toolbox) for SVM was used in the MATLAB environment in this study [36].

3. NB

NB is a simple probabilistic classifier based on Bayes theorem with an intense independence assumption [37]. In human motion recognition, NB is necessary to calculate the Probability Density Function (EDF) of each feature and then calculate the posterior probabilities that the tested sample belongs to different categories. Function `fitcnb` (Statistics and Machine Learning Toolbox) for NB was used in the MATLAB environment in this study [38].

4. Logistic Regression

Logistic Regression is the process of modeling the probability of discrete outcomes for a given input variable. The standard Logistic Regression models binary outcomes, which take two values: true/false and yes/no. Polynomial Logistic Regression can model the situation where there are more than two possible discrete results [39]. Function `fitclinear` (Statistics and Machine Learning Toolbox) for Logistic Regression was used in the MATLAB environment in this study [40].

5. DT

DT is a supervised machine learning technique used to derive Decision Trees from training data [41]. DT is a predictive model, expressed as a recursive division from the feature space to the subspace that forms the prediction basis [42]. DT is a directed tree with roots. In the tree structure, leaves represent categories, non-leaf nodes are features and branches represent a collection of features that lead to the classification [41]. Function `fitctree` (Statistics and Machine Learning Toolbox) for DT is used in the MATLAB environment in this study [43].

6. ANN

ANN is a computational model that simulates the structure of brain neurons for information processing. It consists of an input layer, one or more hidden layers and an output layer. Each layer contains many neurons, and each neuron contains an activation function [44]. In the study, two commonly used ANN, Back Propagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN), were used as classifiers to train and classify motions.

- BPNN is a multilayer feedforward network trained according to the error backpropagation algorithm. It has an excellent ability to approximate any continuous function and healthy nonlinear mapping function [14]. In this study, BPNN is constructed with three layers. The first layer is the input layer. The number of neurons is equivalent to the dimension of the feature vectors; the second layer is the hidden layer. The tangent sigmoid equation is applied as the activation equation:

$$f(x) = \frac{2}{(1 + e^{-2x})^{-1}} \quad (10)$$

The third layer is the output layer. The number of neurons is equal to the number of classified motions, and the activation equation is the tangent sigmoid equation. The basic architecture diagram is shown in Figure 4.

Figure 4. The basic architecture diagram of BPNN.

- A BPNN has a large amount of calculation and processing time [45]. The RBFNN is also a kind of feedforward network that is trained by using a supervised training algorithm, but the calculation and processing time is lower than that of BPNN. The main advantage of the RBFNN is that it has only one hidden layer and uses the radial basis equation as the activation equation [46]. The basic architecture of RBFNN is the same as the basic architecture of BPNN, which contains three layers, namely input, hidden and output layers, as shown in Figure 4. Unlike BPNN, the Gaussian equation is used as the basic equation; therefore, in RBFNN, the general formula for the output of the RBFNN is expressed as follows:

$$f(x) = \sum_{i=1}^M w_i \exp\left(-\frac{\|x - c_i\|^2}{d^2}\right) \quad (11)$$

7. 1D-CNN

CNN, one of the representative deep learning algorithms, is a Feedforward Neural Network with convolutional calculations and deep structure [47]. The main structure of CNN includes the input layer, hidden layer and output layer. There are main structures in the hidden layer: the convolutional layer, the pooling layer and the fully connected layer [47]. CNN can process data of different dimensions (1D-CNN, 2D-CNN and 3D-CNN). Among them, 1D-CNN can receive one-dimensional vectors through the input layer [48]. In this study, the extracted features were input into 1D-CNN as one-dimensional vectors for supervised learning. The basic architecture diagram of 1D-CNN is shown in Figure 5.

Figure 5. The basic architecture diagram of 1D-CNN.

2.4.2. Evaluation

For a specific dataset, most studies use cross-validation and statistical testing to compare the performance of classifiers. Cross-validation can effectively use limited data to find suitable model parameters and prevent overfitting. In cross-validation, the dataset is grouped in a certain way: one part is used as the train set, and the other part is used as the test set. First, the train set is used to train the classifier, and then the test set is used to evaluate the classifier on the trained model. Cross-validation methods include K-fold cross-validation and leave-one-out validation. The commonly used 10-fold cross-validation was applied in this study. In this study, the classification results are presented in a confusion matrix and recognition accuracy. The confusion matrix shows the degree of confusion between different actions. The recognition accuracy is used to evaluate the classification effectivity of the classifier:

$$\text{Accuracy} = \frac{\text{Number of correctly classified}}{\text{overall sample size}} \quad (12)$$

2.5. Recognizing Motions of Baduanjin

In this study, motion recognition used the extracted features from the motion to train classifiers to classify motions. Different classifiers were applied, and their suitability was verified for the motion recognition of Baduanjin. The classifiers were the same as those used to assess motion accuracy, namely *k*-NN, SVM, NB, Logistic Regression, DT and ANN (BPNN and RBFNN). The method of motion recognition is similar to assessing the motion accuracy of Baduanjin.

3. Materials and Methods

3.1. Extracting Features and Dimensionality Reduction

A total of 55 participants were recruited in two batches to participate in the study. In the first batch, 20 participants were recruited to collect the IMU data with 60 sets (three times for each participant). In the second batch, 35 participants practiced Baduanjin motions once to measure motion data. Thus, a total of 95 sets of data with a dataset of $95\text{-set} \times 8\text{-motions} = 760\text{-motions}$. All participants gave their informed consent for inclusion before they participated in the study.

There were 17 skeleton points measured by Perception Neuron 2.0 used in this study. The features extracted by a motion sequence are 306. By using PCA to reduce the dimensionality of features with the error is less than 5%, the dimension can be reduced from 306 to 96. The first three features of the eight motions of Baduanjin are shown in Figure 6.

Figure 6. The first three features of the eight motions of Baduanjin.

3.2. Assessing Motion Accuracy of Baduanjin

Before performing the motion assessment, two traditional Chinese sports teachers from a university in Southwest China were invited to give the scores for the motion accuracy. The teachers have more than ten years of experience teaching Baduanjin in the university, and they were required to score each student's motion based on recorded videos. Each motion was scored according to three categories: Fail, Pass and Good. To ensure the consistency of assessment, the Kendall correlation coefficient test was used to calculate the correlation between scores on motion accuracy of students from the two teachers. The results are shown in Table 2.

Table 2. The grading by two teachers and the Kendall correlation of the scores.

Motions	Teacher A			Teacher B			Kendall Value
	Good	Pass	Fail	Good	Pass	Fail	
Motion-1	16	57	22	15	55	25	0.941
Motion-2	21	53	21	24	50	21	0.882
Motion-3	26	58	11	23	49	23	0.831
Motion-4	22	58	15	19	49	27	0.824
Motion-5	20	57	18	20	56	19	0.838
Motion-6	23	55	17	20	54	21	0.907
Motion-7	29	59	7	26	62	7	0.944
Motion-8	61	34	0	61	34	0	0.862

From Table 2, we can see that the captured motions of Baduanjin from students have three different levels of motion accuracy, namely Fail, Pass and Good, except for Motion-8, where no student failed in this motion. According to the two teachers, this is because Motion-8 is the simplest motion in Baduanjin and easy to learn (Figure 7). Students can master the essentials of Motion-8 through short-term learning, but long-term practice is needed to achieve high motion accuracy. Moreover, the Kendall coefficient between the scores from the two teachers ranged from 0.824 (Motion-3) to 0.944 (Motion-7). This result indicates that the two teachers have a high degree of consistency in the scores of the students' motion accuracy.

Figure 7. Motion-8.

On scores of teachers, through the application of 10-fold cross-validation, the effectiveness of different classifiers was trained and verified to assess the motion accuracy. The accuracy of motion assessment of different classifiers, using scores from Teacher A, is shown in Table 3. Using Motion-1 as an example, the confusion matrices for different classifiers for Motion-1, using scores from Teacher A, are shown in Figure 8.

Table 3. Accuracy of motion assessment of different classifiers, using scores from Teacher A.

Classifiers	Accuracy (%)							
	Motion-1	Motion-2	Motion-3	Motion-4	Motion-5	Motion-6	Motion-7	Motion-8
<i>k</i> -NN	89.47 ¹	92.63 ¹	91.58 ¹	92.63 ¹	89.47 ¹	92.63 ¹	87.37	88.42 ¹
SVM	89.47 ¹	84.21	80.00	92.63 ¹	80.00	75.79	95.79 ¹	80.00
NB	81.05	83.16	74.74	90.53	77.89	80.00	82.11	76.84
Logistic Regression	78.95	71.58	62.11	81.05	84.21	77.89	81.05	76.84
DT	73.68	65.26	65.26	61.05	65.26	62.11	73.68	65.26
BPNN	73.68	61.05	63.16	70.53	78.95	66.32	81.05	73.68
RBFNN	83.16	67.37	75.79	75.79	78.95	75.79	84.21	70.53
1D-CNN	74.74	71.58	76.84	69.47	76.84	88.42	91.58	78.95

¹ The highest accuracy.

The accuracy of motion assessment of different classifiers, using scores from Teacher B, is shown in Table 4. Using Motion-1 as an example, the confusion matrices for different classifiers for Motion-1, using scores from Teacher B, are shown in Figure 9.

Table 4. Accuracy of motion assessment of different classifiers, using scores from Teacher B.

Classifiers	Accuracy (%)							
	Motion-1	Motion-2	Motion-3	Motion-4	Motion-5	Motion-6	Motion-7	Motion-8
<i>k</i> -NN	89.47 ¹	86.32 ¹	88.42 ¹	91.58 ¹	91.58 ¹	86.32 ¹	85.26	86.32 ¹
SVM	83.16	72.63	74.74	86.32	83.16	84.21	87.37 ¹	73.68
NB	78.95	78.95	68.42	88.42	80.00	81.05	84.21	75.79
Logistic Regression	78.95	71.58	62.11	81.05	84.21	77.89	81.05	76.84
DT	73.68	65.26	65.26	61.05	65.26	62.11	73.68	65.26
BPNN	73.68	61.05	63.16	70.53	78.95	66.32	81.05	73.68
RBFNN	83.16	67.37	75.79	75.79	78.95	75.79	84.21	70.53
1D-CNN	72.63	72.63	62.11	76.84	80.00	87.37	81.05	78.95

¹ The highest accuracy.

Tables 3 and 4 show that, where the scores of Teacher A and Teacher B were used as the supervision for training classifiers, *k*-NN has the best accuracy for all types of motions, except for Motion-7. The accuracy for motion assessment on all motions (except Motion-7) is over 86%. However, for assessing the motion accuracy of Motion-7, the results show that SVM has the highest accuracy, reaching 95.79% (for Teacher A) or 87.37% (for Teacher B). It is found from the confusion matrixes that, for the classifiers, *k*-NN and SVM, which achieved higher accuracy, the confusion in the assessment of motion accuracy on Motion-1 mainly occurs between Pass and Fail.

Besides the accuracy of evaluation, for practical applications, the processing time for each classifier is verified in this study. The processing time of different classifiers for evaluating motion accuracy is shown in Table 5.

Figure 8. The confusion matrices of different classifiers for Motion-1, using scores from Teacher A.

Figure 9. The confusion matrices of different classifiers for Motion-1, using scores from Teacher B.

Table 5. Processing time of different classifiers for assessing motion accuracy.

Classifiers	Processing Time (s)
<i>k</i> -NN	0.008 ¹
SVM	4.751
NB	0.021
Logistics regression	0.020
DT	0.010
BPNN	7.709
RBFNN	0.063
1D-CNN	9.179

¹ Minimum processing time.

For the processing time from Table 5, the processing time of *k*-NN is the shortest among the eight classifiers (the processing time is 0.008 s). Moreover, the processing time of SVM is the second longest, which needs 4.751 s to complete the calculation.

3.3. Recognizing Motions of Baduanjin

Applied 10-fold cross-validation, accuracy and processing time of motion recognition on different classifiers are shown in Table 6. The confusion matrices of motion recognition on different classifiers are shown in Figure 10.

Figure 10. Cont.

Figure 10. Cont.

True Class	motion 1	90		5						94.7%	5.3%
	motion 2		95							100.0%	
	motion 3	1		94						98.9%	1.1%
	motion 4				95					100.0%	
	motion 5					95				100.0%	
	motion 6						95			100.0%	
	motion 7							95		100.0%	
	motion 8								95	100.0%	
		motion 1	motion 2	motion 3	motion 4	motion 5	motion 6	motion 7	motion 8		

Predicted Class
(d)

True Class	motion 1	70	2	17	2		2	2		73.7%	26.3%
	motion 2	3	80	6	1	1	2	2		84.2%	15.8%
	motion 3	20	4	58	2		4	7		61.1%	38.9%
	motion 4	1	4	1	83		1	3	2	87.4%	12.6%
	motion 5			1	1	89		1	3	93.7%	6.3%
	motion 6	3	2	1		1	88			92.6%	7.4%
	motion 7	1	2	4	2	1	3	81	1	85.3%	14.7%
	motion 8					2			93	97.9%	2.1%
		motion 1	motion 2	motion 3	motion 4	motion 5	motion 6	motion 7	motion 8		

Predicted Class
(e)

Figure 10. Cont.

True Class	motion 1	80	14	1					84.2%	15.8%
	motion 2	4	81	9			1		85.3%	14.7%
	motion 3	1	13	67	12	2			70.5%	29.5%
	motion 4			3	90	1	1		94.7%	5.3%
	motion 5				1	91	3		95.8%	4.2%
	motion 6					6	87	2	91.6%	8.4%
	motion 7					2	11	74	77.9%	22.1%
	motion 8							4	95.8%	4.2%
		motion 1	motion 2	motion 3	motion 4	motion 5	motion 6	motion 7	motion 8	
		Predicted Class								(f)

True Class	motion 1	63	26	6					66.3%	33.7%
	motion 2	6	62	22	3	2			65.3%	34.7%
	motion 3		17	58	15	3		2	61.1%	38.9%
	motion 4			1	78	13	3		82.1%	17.9%
	motion 5				7	71	14	3	74.7%	25.3%
	motion 6				1	10	71	13	74.7%	25.3%
	motion 7						14	80	84.2%	15.8%
	motion 8							4	95.8%	4.2%
		motion 1	motion 2	motion 3	motion 4	motion 5	motion 6	motion 7	motion 8	
		Predicted Class								(g)

Figure 10. Cont.

Figure 10. The confusion matrices of motion recognition on different classifiers: (a) *k*-NN, (b) SVM, (c) NB, (d) Logistics regression, (e) DT, (f) BPNN, (g) RBFNN and (h) 1D-CNN.

Table 6. Accuracy and processing time of recognizing motions on different classifiers.

Classifiers	Accuracy (%)	Processing Time (s)
<i>k</i> -NN	97.63	0.055 ²
SVM	99.47	0.914
NB	97.89	0.174
Logistics regression	99.21	0.407
DT	84.47	0.087
BPNN	86.97	13.270
RBFNN	75.53	0.295
1D-CNN	99.74 ¹	80.958

¹ The highest accuracy. ² Minimum processing time.

Table 6 and the confusion matrixes in Figure 10 show that, among the eight different classifiers, the accuracy of motion recognition of Baduanjin by four classifiers is over 95%. Overall, 1D-CNN has the highest recognition accuracy, with 99.74%. The recognition accuracy of 1D-CNN for all motions is between 98.9% (motion 1 and motion 3) and 100%. However, the two classifiers of ANN were not satisfactory (86.97% and 75.53%), as they did not reach 90% accuracy. Furthermore, from the confusion matrix, it is found that, for classifiers with high accuracy (*k*-NN, SVM, NB, Logistics regression and 1D-CNN), the confusion between motions mainly occurs between Motion-1 and Motion-3. The reason could be that Motion-1 and Motion-3 are mainly upper-limb movements and relatively similar.

In terms of processing time for the motion recognition, *k*-NN recorded the shortest time among the eight classifiers (0.055 s). In contrast, the longest processing time is 1D-CNN (80.958 s), followed by SVM (0.917 s).

4. Discussion

When students learn the motions of Baduanjin, it would be advantageous to know the accuracy of the motions in real time, so that they can make the correction immediately. However, due to the high student–teacher ratio, students are unable to know the accuracy of motions during the teaching and learning process. On the other hand, given the unique motion characteristics of Baduanjin, it is difficult to assess the accuracy of students' motions without an experienced teacher. Therefore, the study aimed to use IMU to obtain motion data to assess the accuracy of students' motions of Baduanjin. For assessing motion accuracy, some studies have transformed it into comparing the assessed motions with the standard motions [8,49]. For example, Chen et al. [8] used one sequence-based method to assess motion accuracy for another traditional Chinese martial art, namely Tai Chi. They applied DTW to calculate the difference of the motion data between students and teachers to assess the motion accuracy of Tai Chi, and the correlation of assessment to teachers was about 80%. However, in teaching traditional Chinese sports, such as Baduanjin, the motion accuracy is assessed by using the grade scoring method, which means that assessing the motion accuracy of Baduanjin is one classifier problem. In this study, on the extracted time-domain features of the motion data, the assessment results of teachers were used as the motion classification criteria to train the classifiers. From the study results, it can be seen that some classifiers can have the capability to be close to a teacher's assessment. Among the selected classifiers, k -NN has the best accuracy of classification, whether it is trained by using scores from Teacher A or Teacher B as the standard. The lowest accuracy of assessing the eight motions of Baduanjin on k -NN reached 86%. However, k -NN does not achieve the highest accuracy entirely when assessing the eight motions of Baduanjin. The accuracy of SVM in Motion-7 is higher than that of k -NN. Nevertheless, the problem of SVM is that the processing time of SVM is much longer than that of k -NN. The processing time of k -NN is the least of the seven selected classifiers, i.e., only 00.8 s. Therefore, the current study results show that, when assessing the motion accuracy of Baduanjin, k -NN as a classifier is the best choice in terms of accuracy and processing time.

Traditional Chinese martial arts, including Baduanjin, require that the sequence of motions must be followed. The recognition of motions helps students find out whether there are errors in the sequence of motions when they are learning and practicing Baduanjin. The recognition result of the study shows that 1D-CNN has the highest accuracy to recognize the motions (99.74); however, this classifier has problems classifying Motion-1 and Motion-3. Another classifier, SVM, is slightly different from 1D-CNN on the accuracy (99.47%), but the average processing time (0.914 s) of SVM is much less than 1D-CNN. The shortest processing time is k -NN, and the accuracy also reached 97.63%. Therefore, if only considering the accuracy of recognizing motion, 1D-CNN is the best classifier. However, if the accuracy and processing time are taken into account, SVM is better than 1D-CNN to meet the needs of practical application.

From the results, the accuracy of two commonly used ANN, namely BPNN and RBFNN, in motion recognition and motion assessment is not recommended. For example, the accuracy of RBPNN and BPNN in motion recognition is only 86.97% and 75.53%, respectively. Besides, BPNN also has the disadvantage that the processing time is much longer than other verified classifiers. The low accuracy of the two ANN classifiers may be caused by the insufficient sample size, which is one of the limitations of the study.

Moreover, we used the type of sample-based method for assessing motions and recognizing motions, and there is another type of sequence-based method which is not involved in this study [17]. It needs to be tested in future research to compare which of the two types of methods is more suitable for assessing and recognizing motions of Baduanjin.

5. Conclusions

The results show that, when using the extracted features of the motion data captured by IMU, an appropriate classifier needs to be selected that can effectively assess the motion

accuracy of Baduanjin and recognize motions. Its adaptation/extension is to assess motion accuracy and recognize motions for other traditional Chinese martial arts.

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