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Intelligent Recognition of Physical Education Teachers' Behaviors Using Kinect Sensors and Machine Learning

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In this research, Kinect sensors were used to obtain body posture data of physical education (PE) teachers during simulated classes and in combination with classical algorithms of machine learning, to achieve the intelligent recognition of the classroom teaching behaviors of PE teachers. Kinect 1.0 was used to test 10 PE teachers without students during simulated classes, and the characteristics of body postures corresponding to different teaching behaviors during the classes of PE teachers were obtained through time sampling. The accuracy of the light gradient boosting machine (LightGBM) recognition model combined with the Kinect sensor was 0.998, which was significantly higher than those of other algorithms. The combination of Kinect sensors and machine learning enabled the intelligent classification of, for example, password teaching, language explanation, action demonstration, and guiding behavior during a simulated class of PE teachers. The recognition models trained by LightGBM were the most effective.

1. Introduction

Physical education (PE) classroom teaching behavior is a direct reflection of PE philosophy and teaching methods and approaches, and is one of the most important indicators for evaluating PE teaching ability and teaching standards. Traditional quantitative research on PE classroom teaching behavior cannot be achieved on a large scale because of the great amount of manual labour and effort required. The continuous development of machine vision and artificial intelligence (AI) technology has provided new ideas for the research of teaching behavior in PE classrooms. The intelligent recognition of PE classroom teaching behavior will also become one of the main tools of PE teaching research.

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The development of AI, represented by machine vision, has provided new ideas and methods for the study of PE classroom behavior. However, a literature search did not reveal any relevant literature on the study of the intelligent recognition of teaching behavior in PE classrooms. Although there is a lack of research on the use of AI to examine PE classroom behavior, there has been some progress in the field of educational research on the intelligent recognition of the classroom behavior of teachers and students in other subjects. For example, in the study of the behavioral performance of students, Luo and Zhang(1) used a combination of both natural language processing and technological face recognition techniques to accomplish the intelligent recognition of the specific behaviors of students, such as happy, surprised, confused, and distracted, in the classroom and also proposed a corresponding evaluation scheme. In their research, Jia *et al.*(2) also developed a teacher-student interaction assessment system in which the intelligent analysis of student position changes and the intelligent recognition of students' expressions and body postures were implemented. In a study on the application of AI technology in PE classroom teaching, Liu *et al.*(3) constructed feature indicators for classroom teaching behavior recognition and implemented intelligent recognition by the student–teacher (S–T) classroom interaction analysis system on the basis of indicators such as the number of faces and frame difference values, and the results showed that the classical algorithm had the highest accuracy rate of decision trees. In regard to the processing of classroom teaching videos, Zhou *et al.*(4) extracted and transformed the picture and audio features of classroom teaching in an experimental study on different platforms and algorithms, respectively, and achieved satisfactory teaching behavior recognition results. In conducting behavioral research in the classroom, Wei *et al.*(5) and Wang and Wang(6) studied different types of student behavior using target detection algorithms; they also obtained satisfactory identification results. Using a modified version of the Openpose algorithm, Su and Wang(7) processed a classroom video, obtained two-dimensional coordinate data of the 18 joint points of students and achieved the recognition of six types of typical student behavior by means of a constructed somatic recognition model. In the study of the classroom performance behavior of students, Lin *et al.*(8) combined human joint point and image information to recognize specified types of student behavior. Zhang *et al.*(9) extracted the depth image from a Kinect infrared sensor and used a support vector machine (SVM) classifier for classification and recognition to complete the recognition of three types of student body posture.

In summary, a great deal of research has been achieved in the application of the intelligent recognition of classroom teaching behaviors. The initial face recognition has gradually developed into gesture recognition, the image material has developed from the initial grey-scale images to deep images, and the selection of indices has also evolved from the initial single index to the development of diversified indices.

The use of the combination of image processing and machine learning to build the teaching behavior recognition model has become the main method of classroom teaching behavior research. Many classical machine learning algorithms have been applied to classroom teaching in terms of teacher and student face and gesture recognition to obtain classroom teaching behavior data. However, these research results are still inapplicable to different disciplines and types of classroom teaching scenario, and even less so to PE classroom behavior scenarios because of distinct disciplinary characteristics in terms of teaching format and environment.

In this study, we start by examining the disciplinary characteristics of the teaching behavior of PE teachers. Then, we acquire the 3D data of the body joints of PE teachers in simulated classes using a Kinect sensor and collect the dataset of their classroom teaching behaviors. Intelligent recognition models of the classroom teaching behaviors of PE teachers are then trained using various classical machine learning algorithms, and the optimal model is selected by comparing the accuracy rates of the machine learning algorithms. Finally, the intelligent recognition and classification of the classroom teaching behaviors of PE teachers are accomplished with high accuracy.

2. Methods

2.1 Subjects

Ten primary school PE teachers were selected for this study to test the process of simulating lessons. The teachers selected were all young teachers, five of whom had an intermediate title and five a junior title. The ten teachers were required to teach the same content and devise 30-min lesson and teaching tool preparation processes before the test.

2.2 Technical background

The system framework designed for this study is shown in Fig. 1 and consists of three modules: a data acquisition module based on the Kinect sensor, a data processing module based on the Kinect SDK, and a model building and classification module based on machine learning.

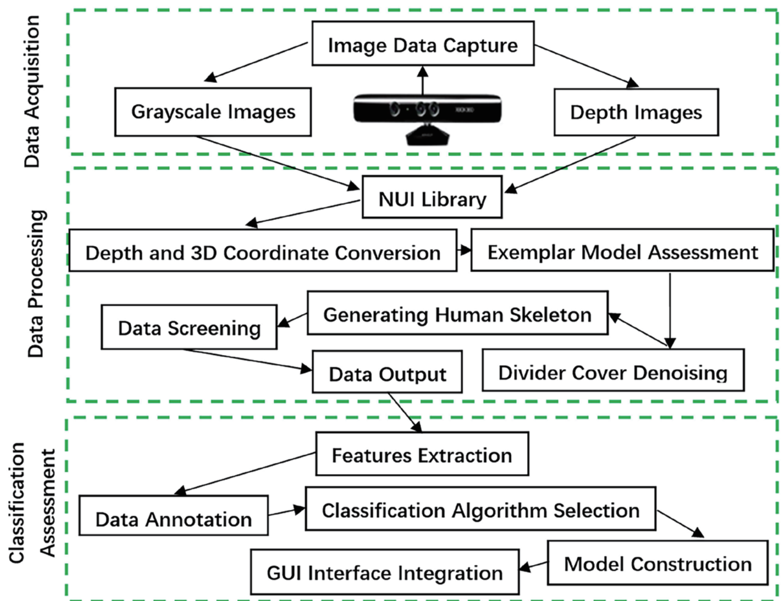

Fig. 1. (Color online) System flowchart.

2.3 Hardware and software needs

The test environment for this study is a SHINELON t2ti laptop with a Core i7-8750H CPU and a Windows 10 64-bit flagship operating system. The system contains 16 GB of 2666 MHz memory and an Nvidia GeForce GTX 1050 Ti (4 GB) graphics card.

2.3.1 Hardware

The test instrument used in this study is the Kinect sensor version 1.0, a 3D body camera released by Microsoft in June 2010, that uses the phase difference measurement of active infrared light round-trip times to acquire depth image data of the human body, used in combination with an RGB camera device. The Kinect sensor integrates several sensors including a camera for human facial expression recognition, two infrared transmitters and receivers for human movement recognition, and a microphone. It is capable of both voice recognition and collecting parameters such as color video, depth video, and skeletal information at the same time. Table 1 shows the hardware parameters associated with the Kinect sensor.

2.3.2 Software

The software platform is Python version 3.7 and Visual Studio 2015 with Kinect SDK, the Kinect companion software.

2.4 Test environment setup

A Kinect infrared camera is used to test and record the simulated lessons of the ten PE teachers. The duration of each simulated lesson was set at 10 min or less, and an alarm clock was set to indicate the end of the lesson. During the test, to ensure the accuracy and integrity of the data obtained, as well as the distance requirements of the test environment and Kinect sensor, we asked the teachers being tested to complete the entire course within the specified space.

For this reason, we designed the distance between the Kinect sensor and the center of the teacher's specified area to be 3.0 m, and the distance between the distal end of the lecture area and the test device to be 4.0 m, ensuring that the acquisition device was directly at the center of the teacher's lecture area. A schematic of the scenario is shown in Fig. 2.

Table 1
Kinect sensor hardware parameters.

Content	Parameter
Test range	0.8–4 m
Perspectives	57° horizontally, 43° vertically
FPS	12, 15, 30
Depth resolution	VGA (640 × 480), QVGA (320 × 240)
RGB resolution	XSGA (1280 × 960), VGA (640 × 480)
Sound format	16 kHz, 32-unit soundtrack pulse code modulation (PCM)

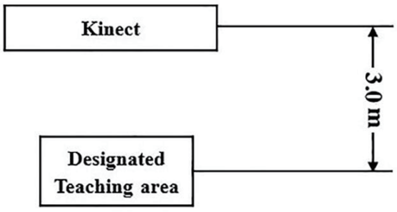

Fig. 2. Schematic diagram of the experimental scene.

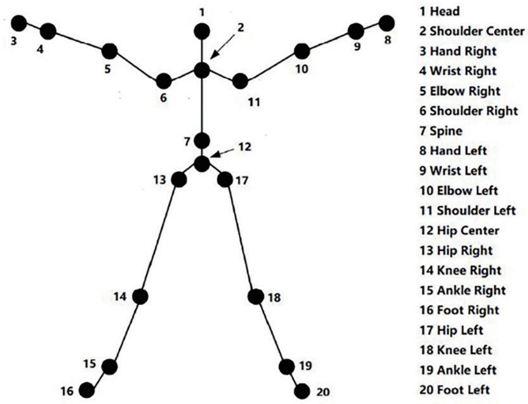

Fig. 3. Body joint points selected for this study.

2.5 Collection and processing of data of classroom teaching behaviors of PE teachers

For body posture recognition, the evaluation model trained with the data of the positions of the coordinates of the body joints is mainly used. The system-style predefined recognition model can accurately obtain the three-dimensional coordinate data of 20 body joint points of the PE teacher during the simulated class using the infrared and depth image data from the Kinect sensor. The selected human body joint points are shown in Fig. 3.

The Kinect sensor is used to acquire a video of the teacher in a simulated class, and the depth image corresponding to the video is processed and used to identify the class of each joint of the body and the spatial location where the physical activity of the PE teacher is located by the Exemplar classification algorithm. The coordinates of each frame of the acquired depth image are converted to actual X, Y, and Z coordinate units, and then the noise processing of the depth image is carried out. Because of the sensitivity of the depth image to the noise of the environment, it is necessary to create segmentation masks during the acquisition of the depth image to filter the background environment of the depth image. Through the noise reduction and creation of segmentation masks, the 3D spatial coordinates of the 20 key joint points of the teacher in each frame can be extracted from the simulated classroom video.

2.6 Data processing and selection of evaluation indicators

The body posture data corresponding to the teaching behaviors of teachers were transferred to comma-separated value (CSV) files, and the body posture data corresponding to their classroom teaching behaviors were labelled in accordance with the differences in body posture changes observed by the human eye. Each row in the labelled CSV file represents all the data of one behavior, where the first column is label data and the other columns are feature data, which are the coordinate data in the 3D space corresponding to each joint point of the body. The classical learning algorithm is selected to train and validate the dataset of body postures corresponding to different teaching behaviors of PE teachers in classroom teaching, and the trained models are compared and evaluated on the basis of the corresponding evaluation criteria. For the evaluation of recognition models, we use the common indicators of evaluation models, such as accuracy (*Acc*), precision (*P*), and recall (*R*), to evaluate and compare the effects of recognition models trained by four classifiers. These relevant indicators are calculated as shown below.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$P = \frac{TP}{TP + FP} \tag{2}$$

$$R = \frac{TP}{TP + FN} \tag{3}$$

Here, *TP* denotes true positive cases, *TN* denotes true negative cases, *FP* denotes false positive cases, and *FN* denotes false negative cases.

Considering that precision and recall also affect each other, we use both F_β scores as parameters to evaluate the trade-off between *precision* and *recall*.

$$F_\beta = \left(1 + \beta^2\right) \cdot \frac{Precision \cdot Recall}{\beta^2 \cdot \left(Precision + Recall\right)} \tag{4}$$

When $\beta = 1$, Eq. (4) is called the F1 fraction.

3. Results

3.1 Relationship between teacher behavior and body posture during simulated lessons

For the research of human behavior recognition, scholars from various countries have also proposed many algorithms, but in the process of operation, they are generally classified on the basis of presegmented short videos. The complex video environment contains much interference information and, at the same time, has high requirements for computing power, such as high-performance GPU, which present great obstacles to the research of teaching behavior recognition. Hence, it is unrealistic to complete the recognition of behavior using only the teaching video. The current popular method of classroom teaching behavior recognition is to use statistics of certain features appearing in teaching behavior in teachers or students, such as face, expression, and body gestures, A dataset of these combined features is used for training, and eventually, for forming a teaching behavior recognition model. In general classroom teaching, the teaching behavior features of teachers tend to overlap, making it difficult to achieve ideal results in classroom teaching behavior recognition. However, unlike general classroom teaching, obvious body posture features are observed in classroom teaching by PE teachers, and the video observation of PE teachers' simulated classes reveals that teachers' classroom behaviors can be clearly distinguished by their body postures. Theoretically, the PE teachers' classroom behaviors can be indirectly deduced from their body posture characteristics. For this reason, in this study, we selected a 997 s video of PE teachers' behaviors for a naked-eye observation and classification experiment to test the feasibility of the indirect estimation method of PE teachers' behavioral categories through body posture recognition. Pictures of four categories of teaching behaviors were selected from 10 PE teachers' teaching videos at 1 s intervals, and then the observation method was used to identify the categories of pictures with hidden behavior labels. The results (Table 2) show that the observation method can identify the four categories of PE teachers' teaching behaviors relatively accurately from pictures of PE teachers' teaching, indicating that the method of body posture recognition can be used to indirectly determine the categories of PE teachers' teaching behaviors.

3.2 Model construction for identifying classroom teaching behaviors

3.2.1 Collection of dataset of PE teachers' classroom teaching behavior

With the release of the KTH dataset in 2004, machine vision started to progress in the direction of behavior recognition, and the number of datasets released in the field of behavior recognition has also started to increase in recent years, for example, the KTH dataset (2004),[10] Weizmann dataset (2005),[11] HMDB51 dataset (2011),[12] Olympic sports dataset,[12] and UCF sports action dataset (2010),[13] along with the size of the database and the number of action categories. However, there is no dataset of teaching behaviors related to PE classroom teaching. Therefore, we independently collected datasets of PE teachers' classroom teaching behaviors to study model training effects. The datasets focus on four common classroom teaching behaviors: password teaching, language explanation, action demonstration, and guiding behavior.

In this PE classroom study, the average instructional time of teachers conducting simulated classroom processes is 10 min, and if the video is processed frame by frame, it will generate much computational load and seriously affect the computing speed. For this reason, we adopted the picture sampling of 1 s of teaching behavior. In this way, we obtained data samples for a total of 5773 s of classroom teaching behavior from 10 PE teachers, as detailed in Table 3.

Table 2
Experimental results of judging PE teachers' teaching behaviors by the observation method.

Behavior category	Time (s)	Number of pictures	Number of pictures	Correct rate (%)
Password teaching	97	97	92	94.8
Language explanation	414	414	407	98.3
Action demonstration	187	187	179	95.7
Guiding behavior	259	259	249	96.1

Table 3
Teaching sample data of classroom simulation lessons of 10 PE teachers.

No.	Time (s)	Number of pictures	Password teaching	Language explanation	Action demonstration	Guiding behavior
1	584	584	31	262	124	167
2	562	562	37	273	98	154
3	588	588	34	252	103	199
4	571	571	41	247	125	158
5	568	568	33	245	89	201
6	579	579	37	263	98	181
7	591	591	36	283	96	176
8	581	581	36	260	127	158
9	566	566	29	251	97	189
10	583	583	35	286	109	153
Average	577.3 ± 9.4	577.3 ± 9.4	34.9 ± 3.2	262.2 ± 13.7	106.6 ± 13.2	173.6 ± 17.4
Median (IQR)	580 (15)	580 (15)	35.5 (3.5)	261 (19.25)	100.5 (23)	171.5 (29)
Total	5773	5773	349	2622	1066	1736

3.2.2 Construction of classification model of classroom teaching behaviors of PE teachers

In this study, the data of 5773 preprocessed classroom teaching behaviors of PE teachers were categorized and labeled, where the label data were the category names of the four types of teaching behavior and the feature data were the 3-dimensional spatial coordinate data of body postures during teaching behaviors. 30% of these data were selected as test data and 70% as training sets. To obtain the desired training effect, four training algorithms for classification evaluation, light gradient boosting machine (LightGBM),(14) random forest,(15) decision tree,(16) and SVM(17) were selected to train the dataset of PE teachers' teaching behaviors in this study. The decision algorithm method is a classification method that uses an approximation of discrete function values. LightGBM is a framework for implementing the gradient boosting decision tree (GBDT)(18) algorithm, which supports the efficient parallel training and distributed processing of classification algorithms. SVM is a classification algorithm based on the Vapnik-Chervonenkis (VC) dimensional theory of statistical learning theory and the principle of structural risk minimization, which has a better recognition effect on small sample data.

The dataset in this study was trained by four classification algorithms, and the models trained by the four classifiers were tested using the test set. The results are shown in Table 4. Among the four algorithms, LightGBM shows the highest accuracy, which reaches 0.98. The other three algorithms have relatively insignificant differences in accuracy, which range from 0.81 to 0.85. From the data of specific teaching behavior identification, it can be seen that for password teaching, the four algorithms differed significantly in precision, with LightGBM having the highest (1.00) and the decision tree having the lowest (0.65). For language explanation, the LightGBM and decision tree algorithms had significantly higher values than the other algorithms. For action demonstration and guiding behavior, the precision of LightGBM was significantly higher than those of the other algorithms, and the differences among the other algorithms were insignificant. For password teaching, there is no significant difference between the recall values of the four algorithms. For language explanation, the four algorithms differed

Table 4
Test results of the four classification training models.

Algorithm	Action	*Precision*	*Recall*	F1-score	SUPPORT
LightGBM	Action 1	1.00	1.0	1.00	57
	Action 2	1.00	0.99	1.00	355
	Action 3	0.98	1.0	0.99	192
	Action 4	0.99	0.99	0.99	197
	Accuracy	—	—	1.00	801
	Macro-avg	0.99	1.00	1.00	801
	Weighted avg	1.0	0.99	0.80	801
Decision Tree	Action 1	0.65	0.73	0.69	59
	Action 2	0.96	0.97	0.96	354
	Action 3	0.81	0.83	0.82	198
	Action 4	0.85	0.77	0.81	190
	Accuracy	—	—	0.87	801
	Macro-avg	0.82	0.83	0.82	801
	Weighted avg	0.87	0.87	0.87	801
Random Forest	Action 1	0.86	0.34	0.49	53
	Action 2	0.80	0.99	0.89	361
	Action 3	0.81	0.67	0.74	217
	Action 4	0.85	0.76	0.80	170
	Accuracy	—	—	0.81	801
	Macro-avg	0.83	0.69	0.73	801
	Weighted avg	0.82	0.81	0.80	801
SVC	Action 1	0.76	0.45	0.56	65
	Action 2	0.88	0.98	0.93	363
	Action 3	0.82	0.77	0.80	188
	Action 4	0.85	0.83	0.84	185
	Accuracy	—	—	0.85	801
	Macro-avg	0.83	0.76	0.78	801
	Weighted avg	0.85	0.85	0.85	801

Note: Action 1 denotes password teaching, Action 2 denotes language explanation, Action 3 denotes action demonstration, and Action 4 denotes guiding behavior.

significantly in recall, with LightGBM showing a significantly higher value, as high as 0.99, than the other algorithms. The other algorithms also showed differences in recall value, with the random forest having the lowest value of 0.67. For both action demonstration and guiding behavior, the recall value of LightGBM is significantly higher than those of the other algorithms. For password teaching recognition, the F1-score of LightGBM is significantly higher than those of the other three algorithms, and the difference is very obvious. For language explanation, all four algorithms showed relatively stable data, with LightGBM having the highest F1-score and the other algorithms having insignificant differences. For action demonstration and guiding behavior, the F1-score of LightGBM is significantly higher than those of the other algorithms, while the differences among the other algorithms are insignificant.

The prediction models of the four algorithms were tested separately using the test set. From the confusion matrix (Fig. 4) of the detection results of the recognition models of the four algorithms, it can be seen that the deviation between the true and predicted values of LightGBM is small, and there is only one recognition error of behavior during the whole test, i.e., action

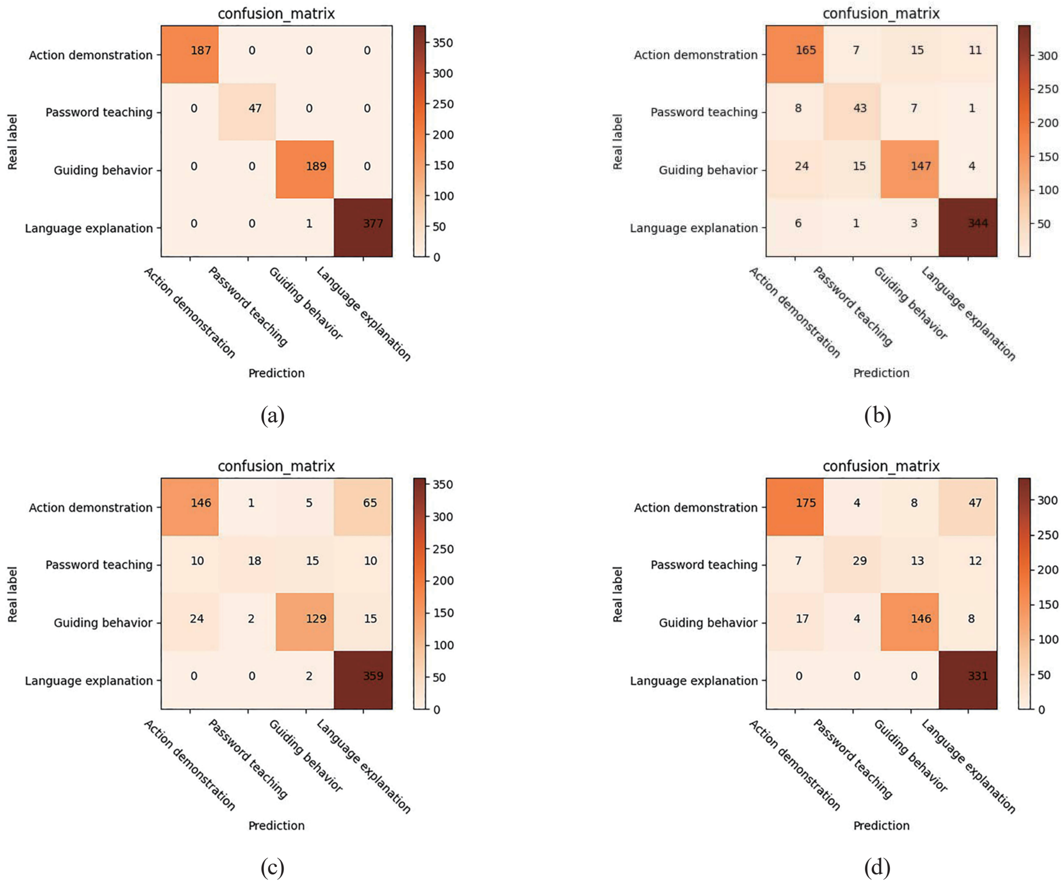

Fig. 4. (Color online) Confusion matrixes corresponding to different recognition models. (a) LightGBM. (b) Decision tree. (c) Random forest. (d) SVC.

demonstration was incorrectly recognized as password teaching. The decision tree, random forest, and SVC algorithms all showed recognition errors of the four behaviors against each other.

4. Discussion

Compared with the teaching of other subjects, there are obvious differences in both the teaching content and teaching method in PE. The selection of the general PE classroom teaching content is usually derived from sports items in competitive sports, and the PE teaching content is formed after the processing of PE materials. For these teaching contents and the special regulations applied to the PE classroom at the site of teaching, it is decided that the teaching of PE comprises a dynamic change in the physical activity process, in which the change in body posture is the main characteristic of the change in the behavior of PE teachers. The assessment of physical education teacher competencies in the form of simulated lessons is similar to the teacher certification exam in the form of regular PE classroom teaching, and changes in teacher behavior will show corresponding changes in body posture characteristics.

Supervised learning is the main means of achieving target classification in the field of machine vision, and the premise of supervised learning is that one can manually label and classify the data of the target. To achieve the intelligent recognition and classification of teaching behaviors, the prerequisite is to be able to classify the teaching behaviors by visual observation. Therefore, through the observation experiments of PE teachers' teaching behaviors, we found that the main teaching behaviors of PE teachers can be clearly identified from the grayscale images of their simulated classes through human–computer interaction. Four classical supervised learning classification algorithms are used to train a classification model on the body posture data of the PE teacher during the simulated class captured by the Kinect sensor, and the training results are tested with a test set. The results show that LightGBM is significantly better than the other algorithms in terms of overall recognition accuracy, as well as in terms of the precision, recall, and F1-score of specific behaviors. There are also few false positive cases of raw recognition results during the test, while the other algorithms all have mutual false recognition samples between categories. Figure 5 shows the training loss function curve of the LightGBM recognition model. It can be seen that as the complexity of the model increases, the training error of the model using the training dataset gradually decreases, indicating that the model does not show the overfitting phenomenon in the training process.

In image processing, the Kinect SDK for the Kinect sensor has an image preprocessing module that generates the coordinates of key body points directly through the module's unique image preprocessing and joint point data generation algorithms. These preprocessing modules will significantly reduce the time and cost of the recognition process, as only 60 sets of body coordinates need to be processed for the recognition of a body pose. In addition, the data processing design of this study is also sampled and makes all four algorithms faster in terms of computing speed. The model trained by LightGBM was selected as the classifier of the teaching behaviors of PE teachers after combining recognition accuracy and computing speed. Compared with other similar research results, the present system has advantages in terms of recognition speed, the number of nodes, and the practicality of the system. For example, compared with

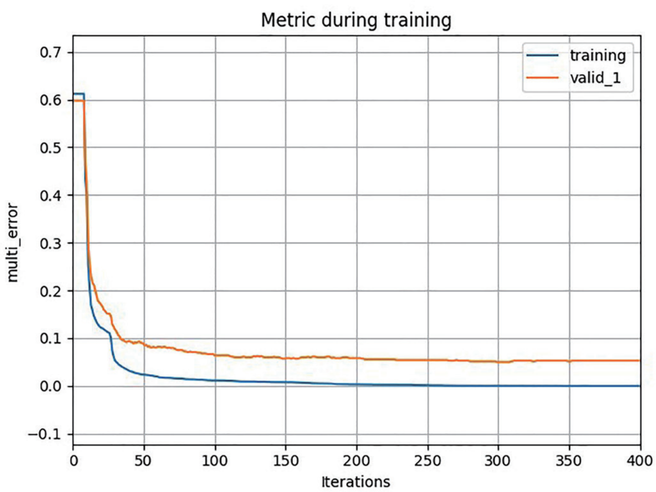

Fig. 5. (Color online) Training loss function curve of LightGBM recognition model.

Zheng's HRNet framework based on the recognition of the teacher's nose and hands,[19] the body posture algorithm-based teaching behavior recognition model trained in this study captured a greater number of body joint point coordinates and was able to recognize more complex physical behaviors.

Compared with the SSD algorithm designed and developed by Zeng[20] for recognizing students' behavioral states in the classroom, our model greatly enhances the practicality of the system as it uses Kinect sensor data for direct processing, which in turn reduces the configuration requirements for running the system.

In summary, the combination of a Kinect sensor and machine learning can be applied to the simulated class scenario of PE teachers, and can achieve high recognition results. However, at the same time, considering the recognition range limitation of the Kinect sensor, the test range of this study can only complete the recognition of teachers' teaching behaviors in prescribed scenes, and data collection can only be done for a single person and is not yet possible with the current hardware support for teaching behavior recognition for multiple people and for teaching behavior recognition that takes place in a larger teaching space.

5. Conclusions

We used a Kinect sensor to acquire joint coordinates of the PE teacher's body postures in a simulated classroom. A classification dataset of teaching behaviors characterized by changes in joint coordinates was collected. An intelligent recognition system was designed and the optimal classification evaluation model was selected through experimental comparison to explore the methods and means of intelligent recognition of PE classroom behavior. The results show that the combination of the Kinect sensor and LightGBM can better classify the behavior of PE teachers in simulated classrooms, and its recognition accuracy reached 0.998. It can provide methodological support for the quantitative evaluation of PE classroom teaching, teaching feedback, and large-scale behavioral research. However, the method still suffers from strict requirements for teaching scenarios and the inability to achieve the simultaneous acquisition of multiple targets.

Acknowledgments

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