A recognition method of learning behaviour in English online classroom based on feature data mining

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Abstract: This paper proposes a recognition method of learning behaviour in English online classroom based on feature data mining. Firstly, with the support of fractal theory, the adjacent search method is used to extract the edge of learning behaviour image, and then the data clustering method is used to reduce the dynamic change range of data caused by edge extraction and improve the degree of data standardisation. Finally, the optimal characteristics of learning behaviour are obtained by Drosophila optimisation algorithm, then the learning behaviour recognition of English online classroom is realised by mining characteristic data. Simulation results show that this method has the highest accuracy of 98% and the comprehensiveness of recognition of different types of learning behaviour can reach 0.95. This method retains the details of behaviour image as much as possible to make it more practical.

Keywords: feature data mining; behaviour identification; proximity search method; fruit fly optimisation algorithm; data clustering.

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1 Introduction

In the field of education and teaching, students' classroom learning behaviour has always been the focus of attention. In the process of classroom learning, students are usually the main body. Therefore, analysing their learning behaviour is of great significance to ensure the quality of classroom teaching (Hallal et al., 2020). In the era of internet intelligence, monitoring and other devices can be used to monitor students' learning behaviour. However, due to the diversity of students' learning behaviour, it greatly increases the difficulty of the research on students' behaviour (Dai et al., 2019). Under the above background, in order to accurately obtain the characteristics of students' learning behaviour, it is necessary to design more perfect behaviour recognition methods, obtain students' learning motivation through the results of students' behaviour recognition, so as to formulate targeted learning plans, so as to achieve the purpose of improving students' learning effect (Yang et al., 2019; Heo et al., 2019).

At present, relevant scholars have conducted comprehensive research on behaviour recognition methods. The commonly used behaviour recognition methods mainly include the following:

In reference (Liu et al., 2019), a behaviour recognition method based on RGB-D and deep learning was proposed, which combined the random forest algorithm with depth information to draw a skeleton map by acquiring human skeleton data. The information presented in the bone map was then translated into a colour map to generate an image with ROI. Finally, the dropout strategy was introduced to identify the features in the image by transforming the VGG network layers. This method can obtain the key information from the static image through image transformation, which is helpful to improve the recognition effect. However, due to the dynamic characteristics of learning behaviours, the method is difficult to accurately identify many learning behaviours. In reference (Zheng et al., 2019), a behaviour recognition method based on deep learning and intelligent programming was proposed. This method classified behaviour images by deep residual network, and then classified depth features of images by recursive neural network. After establishing intelligent programming model, the classification results were transformed, and thus the behaviour sequence was derived. This method has high recognition efficiency, but it has the problem of missing details, which leads to the incomplete recognition results. In reference (Qi et al., 2020), a behaviour recognition method based on context feature fusion was proposed. In this method, the spatial and short-time features of actions were extracted by 3D convolution kernel. After feature fusion, the convolutional neural network was used to learn and train the fused features to obtain the spatio-temporal information. Finally, the behaviour characteristics were classified by Softmax classifier, and the behaviour recognition was realised by combining the training and classification results. This method can obtain the recognition result in a short time, but it has shortcomings in the comprehensiveness of the recognition result.

Through the above analysis, it can be seen that although the traditional methods can realise the rapid recognition of behaviour characteristics, there are some problems such as inaccurate recognition results, incomplete results and easy loss of details. In today's information age, the information contained in the image is very rich. A large amount of detail information can be obtained through image analysis. Therefore, aiming at the above problems, this paper proposes a recognition method of learning behaviour in English online classroom based on feature data mining.

1 With the support of fractal theory, the neighbourhood search method is used to extract the edge of learning behaviour image by sub block matching after determining the neighbourhood search range.

2 Based on the edge information bit object of the extracted learning behaviour image, the dynamic change range of a large amount of data caused by edge extraction is reduced by clustering, and the standardised data is obtained, so as to complete the image pre-processing.

3 Using the Drosophila optimisation algorithm, the learning behaviour recognition process is constructed by obtaining the Drosophila population, searching the target foraging position and learning the behaviour characteristics, so as to obtain the optimal characteristics of the learning behaviour.

4 The characteristics of a certain kind of learning behaviour are obtained through feature data mining, and the mined feature data are fused to obtain the feature saliency map, which is taken as the overall feature data mining result to realise the effective identification of all learning behaviours.

2 Image pre-processing of learning behaviour in English online classroom

Before identifying English online classroom learning behaviour, in order to improve the accuracy of behaviour recognition results, the behaviour image is taken as the research goal and pre-processed. In this paper, five typical online classroom behaviour images of 200 students are collected and pre-processed.

2.1 Extracting edge information of learning behaviour image

The quality of image information directly affects the visual perception effect of learning behaviour recognition. Therefore, in order to enhance the authenticity of recognition results, image Mosaic technology is usually used to process images. However, the technology can not present a sense of space, affecting the recognition effect. To solve this problem, some scholars proposed to construct a 360° 3D scene without dead angle by using multi-angle 2D images collected in real scenes by means of splicing and synthesis (Xia et al., 2020; Luo, 2021). However, this method will consume a lot of time because of the complicated processing steps. Therefore, this paper takes the above factors into full consideration and, with the support of fractal theory, adopts proximity search method to extract edges of learning behaviour images. The specific extraction steps are as follows:

1 The target image is divided into multiple sub blocks, where $L_{\max}$ and $L_{\min}$ represent the maximum side length and minimum side length of the image sub-block, respectively. Taking the sub-block as the image centre, it is adjacent to the search range, it can be expressed as:

$$\Delta S_q = \sum_{i=1}^{N} \sum_{j=1}^{N} \left(L_{\max}^{i} - L_{\min}^{j} \right)^2 \tag{1}$$

Among them, N represents the number of sub-blocks; i and j represent the image space coordinates.

2 Select a sub-block P_k arbitrarily, search for the best matching parent block Q_k, and set the search space in the range of $2^L \times 2^L$.

3 In the search process, set a fractal coding threshold. If the image edge distortion is lower than the threshold, the image edge can be obtained; if the image distortion is higher than the threshold, it is necessary to re select the sub block and repeat the search until the qualified edge is obtained (Lu et al., 2019).

The edge extraction result of learning behaviour image is obtained through the above steps, and the result is used as the basis of behaviour recognition.

2.2 Learning behaviour data pre-processing

Although the above process obtained the results of edge extraction of behaviour image, the resulting large amount of data will bring some difficulties to behaviour recognition.

Therefore, in order to improve the authenticity and validity of the identification results, data pre-processing is used to solve the problem of large differences in data variables (Lentzas and Vrakas, 2020; Sajjad et al., 2020). In this paper, the data clustering method is used to narrow the dynamic range of data.

Use μ_v as the initial data variable generated in the edge extraction of learning behaviour images, use SPSS software to summarise the variables, and use the *Z* clustering method to perform data conversion to obtain the initial cluster centre:

$$D(x) = \Delta S_q(t+1) \times W_{\max} \tag{2}$$

Among them, $D(x)$ represents the initial cluster centre; $W_{\max}$ represents the maximum value of the dynamic change coefficient of the data; *t* represents the Euclidean distance between the data vectors. Through the analysis of formula (2), the data clustering processing formula can be obtained, as follows:

$$G_{ij}^2 = D(x)W_{id} + D(x)W_{jd} \tag{3}$$

Among them, W_{id} represents the uncertainty coefficient of the data cluster boundary; W_{jd} represents the data cluster. Combining formula (3) to further obtain the data clustering centre C_ξ, the specific formula is as follows:

$$C_\xi = G_{ij}^2 \times \frac{\left(\sigma_n^2 \sqrt{y_i^2 + y_j^2}\right)}{\sqrt{y_i^2 + y_j^2}} \tag{4}$$

Among them, σ_n^2 represents the number of uncertain clusters; y_i^2 and y_j^2 respectively represent data similarity and data weight.

Through the above steps, the standard sample data in the data clustering centre can be obtained and expressed in the form of matrix (Wang et al., 2020a):

$$C = \begin{bmatrix} c_{11} & c_{12} & c_{1n} \\ c_{21} & c_{22} & c_{2n} \\ c_{n1} & c_{n2} & c_{nm} \end{bmatrix} \tag{5}$$

Among them, *m* represents the data dimension.

Through the above analysis process, the pre-processing of learning behaviour data is completed, and the standardised data is obtained as the data basis for learning behaviour recognition.

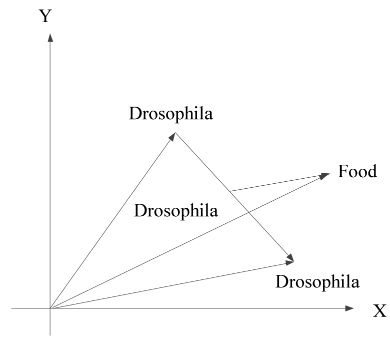
3 Recognition of learning behaviour in English online classroom

3.1 Constructing learning behaviour recognition model

Because the traditional method needs a large number of sample data to be trained in learning behaviour recognition, and the fruit fly optimisation algorithm only needs a small amount of sample data to complete behaviour recognition (Li et al., 2021; Cheung et al., 2019). Therefore, this paper establishes a learning behaviour recognition model in English online classroom through Drosophila optimisation algorithm.

Figure 1 is a schematic diagram of Drosophila foraging in Drosophila optimisation algorithm.

Figure 1 Schematic diagram of fruit fly foraging



According to the foraging behaviour characteristics of fruit flies shown in Figure 1, the process of building a learning behaviour recognition model based on the fruit fly optimisation algorithm is described as the following steps:

Step 1 Acquisition of drosophila population

Set an initial parameter and limit the range of activity of the fruit fly, denoted by (*a*, *b*, *c*), and denoted by d_h as the flight distance of the fruit fly. The initial position of the fruit fly population is expressed as:

$$\begin{cases} a_0 = d_h \times \alpha_h \\ b_0 = d_h \times \beta_h \\ c_0 = d_h \times \gamma_h \end{cases} \tag{6}$$

Among them, α, β and γ all represent position space coordinates.

Step 2 Target location search

If ∂_1 represents the flight direction of fruit flies in the foraging process, φ_z represents the search distance of fruit flies, and formula (7) represents the foraging position of fruit flies:

$$\begin{cases} a_1 = d_h \times (\alpha_h - a_0) \\ b_1 = d_h \times (\beta_h - b_0) \\ c_1 = d_h \times (\gamma_h - c_0) \end{cases} \tag{7}$$

Step 3 Since the specific location of the food source cannot be obtained through step 2, therefore, a taste concentration judgement value T_e is set, and the taste concentration of the food source is judged by this value (Lai et al., 2020):

$$T_e = \frac{P(E|\omega_i) \cdot P(\omega_i)}{P(E)} \tag{8}$$

Among them, ω_i represents the search step length of individual fruit flies; E represents the optimisation ability of fruit flies.

Based on the principle of Drosophila optimisation algorithm, it is applied to learning behaviour recognition, that is, the process of obtaining optimal behaviour characteristics (Wang et al., 2020b). Therefore, the learning behaviour recognition model is expressed by formula (9):

$$U(f) = \exp\left[\tau_{ab}(f) + \tau_{bc}(f)\right] \tag{9}$$

Among them, $\tau_{ab}(f)$ represents the initial image of learning behaviour, as the model input; $\tau_{bc}(f)$ represents the optimal learning behaviour image, as the model output.

3.2 *Recognition of English online classroom learning behaviour based on feature data mining*

Learning characteristic data is a very important indicator in behaviour recognition and an important basis for behaviour analysis. The quality of characteristic data is of great significance to the accuracy of behaviour recognition results. Therefore, based on the construction of the learning behaviour recognition model constructed above, the form of feature data mining is used to further identify the learning behaviour of English online classrooms to achieve the purpose of improving the recognition effect.

Based on the learning behaviour recognition model, the characteristic data of learning behaviour is mined. Because different behaviours have certain differences, and in the behaviour recognition may also produce occlusion, coverage and other situations. So, in order to solve this problem, this paper obtains the characteristics of a certain type of learning behaviour through feature data mining, and realises the effective recognition of all learning behaviours based on the result of feature mining.

Use Gaussian convolution test to down-sample the English online classroom learning behaviour image to obtain different sequence images, $C = \{c_1, c_2, \ldots, c_n\}$, the feature data set of the sequence can be expressed by formula (10):

$$J_C = \frac{1}{m}\sum_{i=1}^{N}\left(\frac{1}{2}h_w\left(x^i - y^j\right)\right) \tag{10}$$

Among them, J_C represents the original feature data set; h_w represents the associated feature data; x^i and y^j represent the correlation features between any two behaviour images. Use the convolution method to extract the even rows and columns in the original feature data set, and then iterate to get the processed feature data set:

$$Z_C = f_{ij}\left(\sum_{i=1}^{N} v_{ki}\right) \tag{11}$$

Among them, v_{ki} represents the discrete points in the feature data set; f_{ij} represents the association rules between the data. The data feature amount obtained by the above mining is relatively large. In order to reduce the number of features and reduce the difficulty of recognition, the feature set is further reduced to obtain an effective data feature set:

$$C' = \left\{c_{1x}, c_{2x}, \ldots, c_{nx}\right\} \tag{12}$$

On this basis, a feature data mining model is established:

$$\omega_{ij}(a+1) = \omega_{ij}(a) - \eta\frac{\omega_{ij}(a)}{\partial_{ij}(a)} \tag{13}$$

Among them, $\omega_{ij}(a)$ represents the feature threshold matching coefficient, that is, model input; $\partial_{ij}(a)$ represents the multi-track feature of learning behaviour, that is, model output; η represents the feature clustering coefficient.

Follow the above steps to obtain a series of learning behaviour features, fuse the feature data obtained by mining, and obtain a saliency map, which is used as the feature data mining result, as follows:

$$F(N) = \frac{2}{[1+\exp(-2N)]-1} \tag{14}$$

In summary, the pre-processing of learning behaviour is realised by establishing a learning behaviour recognition model, so that the edge information of learning behaviour is clearer. On this basis, feature data mining of learning behaviours is carried out to obtain the final recognition results of learning behaviours.

4 Experiment and result analysis

In order to verify the application effect of feature data mining based behaviour recognition method for English online classroom learning, the following experimental analysis process is designed.

In order to improve the persuasiveness of the experimental results, the behaviour recognition algorithm based on RGB-D and deep learning and the behaviour recognition method based on context feature fusion are used as comparison methods.

Table 1 Statistical table of experimental data set information

Behaviour type	*Number of images/frame*
Gesture	247
Hands-on	563
Eye contact	2,871
Answer the questions	146
Do actions that are not related to the classroom	852

4.1 *Experiment preparation*

The images used in the experiments in this article are all from the Weizmann database, which is mainly a human body behaviour database, which contains a total of 90 videos and tens of thousands of behaviour images. Five behaviours of different human targets are extracted from the database as research targets. In order to ensure the validity of the image, the images in the database are all collected under a still lens and under a multi-view angle. Therefore, the accuracy of the experimental results can be guaranteed. Table 1 shows the detailed information of the experimental data set.

4.2 Experimental indicators

In the experiment, in order to highlight the advantages of the proposed method, analysis will be carried out from both subjective and objective levels.

There are two kinds of objective indicators:

1 Accuracy rate of recognition results (%): this indicator mainly reflects whether the recognition results conform to the actual behaviour of students. The greater the accuracy rate, the better the recognition effect. The calculation results of recognition result accuracy are as follows:

$$K = \frac{k_1}{k_2} \times 100\% \tag{15}$$

where k_1 represents the number of accurate recognition and k_2 represents the total number of recognition.

2 Comprehensiveness of the recognition results: this indicator mainly reflects the coverage of the recognition results, which is expressed by a numerical value. The specific interval is (0–1.0). The larger the value, the more comprehensive the recognition result.

3 Subjective indicators: the subjective level is mainly reflected by the contour extraction results of the behaviour image, testing whether the extraction results of the three methods are comprehensive, and checking whether there is a problem of local details loss.

4.3 Experimental results

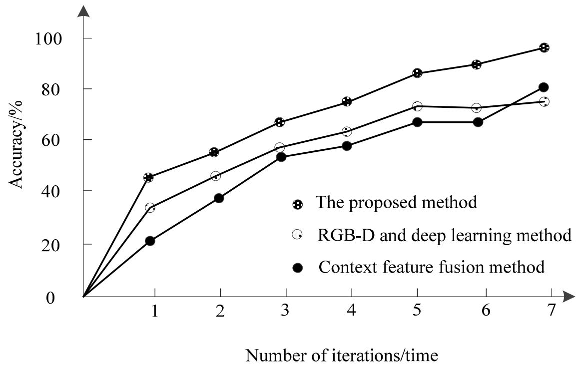
Under the above-mentioned experimental environment and data conditions, the method identification effect test is carried out, and the test results are analysed as follows.

4.3.1 Experiment 1

Test the accuracy of the above three methods of English online classroom learning behaviour recognition, the test results are shown in Figure 2.

According to the test results shown in Figure 2, the accuracy of the recognition results of the three methods in the recognition of English online classroom learning behaviours basically maintains a steady upward trend. Among them, the recognition accuracy of the proposed method is higher, and when the number of iterations is the seventh in the second time, its recognition accuracy rate reached 98%, while the recognition accuracy rate of RGB-D and deep learning methods was 76%, and the recognition accuracy rate of the context feature fusion method was 82%. From the above comparison, we can see that the advantages of the proposed method are more obvious. The reason for this difference is that the proposed method pre-processes classroom learning behaviour images before performing student behaviour recognition. This step not only reduces the recognition time, but also improves the accuracy of the recognition results.

Figure 2 Comparison results of behaviour recognition accuracy



4.3.2 Experiment 2

Test the comprehensiveness of the English online classroom learning behaviour recognition of the above three methods, and the test results are shown in Table 2.

Table 2 Comprehensive comparison results of behaviour recognition

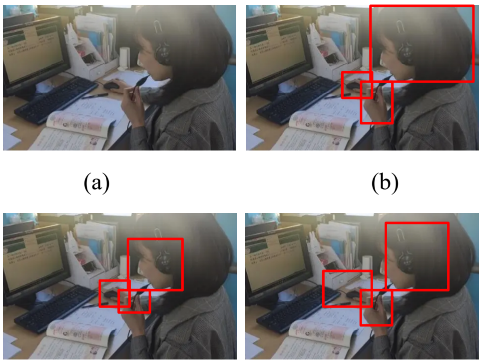
Number of iterations/time	*The proposed method*	*RGB-D and deep learning methods*	*Context feature fusion method*
1	0.95	0.85	0.75
2	0.94	0.82	0.72
3	0.90	0.78	0.79
4	0.89	0.79	0.81
5	0.92	0.80	0.83
6	0.95	0.78	0.86
7	0.92	0.80	0.87

According to the experimental results data in Table 2, the maximum comprehensiveness of the proposed method is 0.95 and the minimum is 0.89; the highest comprehensive value of RGB-D and deep learning method is 0.85, and the lowest value is 0.78; the highest value of the comprehensiveness of the context feature fusion method is 0.87 and the lowest value is 0.72. According to the above data, the identification results of the proposed method are more comprehensive. With the help of this method, we can obtain more comprehensive analysis results of students' learning behaviour. With the help of comprehensive analysis results, we can help student's correct bad learning habits.

4.3.3 Experiment 3

The above-mentioned tests are all from an objective point of view to verify the application effect of the method. The following is a subjective point of view to analyse the recognition results of the three methods, and the simulation results are shown in Figure 3.

Figure 3 Contour extraction result of learning behaviour image, (a) original image, (b) method of this article, (c) RGB-D and deep learning methods, (d) context feature fusion method (see online version for colours)



(a) (b)

(c) (d)

The lines in Figure 3 are the contour extraction results of the learning behaviour image. Analysis of Figure 3 shows that when the proposed method is used to perform the contour extraction test on the learning behaviour image, the contour extraction can be completed accurately and completely without loss of image detail information; When RGB-D and deep learning methods are used for contour extraction test, the image contour cannot be completely extracted, and some key information is lost; when the context feature fusion method is used for contour extraction test, the extraction effect is worse. It can be seen that the contour extraction effect of the proposed method is the best, and the completeness of the contour extraction result is improved.

5 Conclusions

In view of the inaccuracy, incompleteness and easy loss of details of traditional methods, this paper proposes an English online classroom learning behaviour recognition method based on feature data mining. The main innovations of this method are as follows: with the support of fractal theory, this paper uses neighbourhood search method to extract edges of learning behaviour images by sub-block matching. Then the clustering method is used to reduce the dynamic range of the large amount of data caused by edge extraction and standardise the edge data. Because different behaviours have certain differences, and in the behaviour recognition may also produce occlusion, coverage and other situations. Therefore, this study obtains the features of a certain class of learning behaviours through feature data mining, and realises the effective identification of all learning behaviours based on the results of feature mining.

As can be seen from the experimental results, the maximum accuracy of the recognition results of this method is 98%, and the results are relatively comprehensive. The comprehensiveness of the recognition of different types of learning behaviours can reach 0.95, which can contain different types of behaviour types and retain the details of behaviour images as much as possible.

This paper mainly processes the behaviour image in student behaviour recognition. In order to solve this problem, the behaviour image is pre-processed before behaviour recognition. In order to improve the effect of behaviour recognition, research should be carried out from the following aspects: improving the accuracy of recognition results, comprehensiveness of results, and retaining image detail features. Although this method has achieved good application results, it has less analysis on the influencing factors of learning behaviour imaging. Therefore, in the follow-up research, we will strengthen the research, find out the deficiencies in time and solve them in time.

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