

## Retraction

# Retracted: Evaluation of the Students' Learning Status in the Foreign Language Classroom Based on Machine Vision

## **Journal of Robotics**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/ participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation. The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

 L. Yao and Q. Qin, "Evaluation of the Students' Learning Status in the Foreign Language Classroom Based on Machine Vision," *Journal of Robotics*, vol. 2022, Article ID 6432133, 12 pages, 2022.



## **Research** Article

# Evaluation of the Students' Learning Status in the Foreign Language Classroom Based on Machine Vision

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In order to improve the effectiveness of the evaluation of student's learning status in foreign language classrooms, this paper applies machine vision to classroom teaching. Through an in-depth analysis of the relative motion relationship between the end marker points of classroom feature recognition and the center point of the machine vision system window, this paper first proposes an autonomous tracking motion algorithm of the machine vision system window based on the preset field of view parameters. Moreover, this paper realizes the motion function of the window to track the marker points autonomously, completes the simulation analysis through two sets of planned trajectories and two sets of master hands to collect the actual trajectories, and verifies the correctness and feasibility of the algorithm. The research study shows that the algorithm based on machine vision proposed in this paper can effectively judge the real-time state of students in the foreign language classroom.

## **1. Introduction**

Classroom learning is one of the main forms for university students to acquire relevant professional knowledge and there is still a lot of knowledge acquired by undergraduate students through classroom learning. At the same time, classroom learning is also one of the important ways to cultivate students' thinking styles. It is the basis for other teaching links and students' self-study and it enables students to better understand and master how to learn effectively. Moreover, with the foundation of classroom learning, students can expand and extend the space for self-learning, make better use of extracurricular time for learning activities, and promote their comprehensive learning and development. Through the detection of students' classroom learning, it reflects students' absorption and implementation effect of classroom learning and their attitude towards learning and indirectly reflects the learning status of today's college students [1]. The study of undergraduate students' classroom learning status and students' self-evaluation of learning status has a certain significance for understanding the current students' learning psychology, factors affecting

learning, and how to stimulate students' learning motivation and improve students' interest in learning. In addition, it has a certain inspiring effect on the current curriculum teaching reform and the cultivation of innovative talents [2]. In addition, state refers to appearance characteristics and action modality. In literature [3], the author believes that the classroom learning state refers to the sum of the physical characteristics, action behavior, and psychological activities of students in the course of classroom learning due to the combined effect of subjective and objective reasons. Professor Liu Guiqiu divides the classroom learning state of college students into pre-class study preparation state, inclass listening state, and after-class learning effect state. In literature [4], the author believes that the state of classroom learning refers to the process of listening, thinking, and teacher-student interaction in the classroom. Moreover, he believes that all aspects of preparation or preview before class, as well as learning effect and review after class, are only the learning state closely related to students' classroom learning state. The two should be distinguished. The learning state is a broader state, which includes the classroom learning state, pre-class learning, and after-class learning.

However, the classroom learning state is a state with limited conditions, which refers to the learning state in the course of listening to the class [5]. At the same time, classroom learning status cannot represent the learning status of students. This research investigates and analyzes students' classroom learning status, after-school learning status as an extension of classroom learning, the detection mechanism of classroom learning effect evaluation, and students' selfevaluation, so as to provide a reference for improving students' learning status, improving teachers' teaching quality, and promoting the improvement of school teaching level [6].

With the support of a series of emerging technologies such as smart classrooms, online learning platforms, and "artificial intelligence + education", learning methods have shown diverse characteristics. Traditional face-to-face teaching methods are constantly being challenged, and online teaching methods that span spaces have become a new wave. Online learning realizes the push of educational and teaching resources through Internet technology, breaking the limitations of time and space on learners' learning [7]. The significance of online learning is not only to create a learning method across time and space but also to enable more high-quality educational resources to be shared by the majority of learners through the Internet and to provide learners with personalized teaching services. Today, online learning has become one of the most important ways of learning and online learning status is one of the important factors affecting learners' online learning performance, and it is also a problem that education researchers cannot ignore [8]. Through the use of analysis and evaluation technology, it is of great significance to objectively evaluate the learning status of online learners for improving teaching quality and learning efficiency. Therefore, more and more educational researchers are paying more and more attention to online learning status and its related evaluation research. The learning state is the sum of the attention state, emotional state, motivational state, and so on shown by the learner in the learning process and learning results [9]. The complexity of the learner's learning state determines that the researcher cannot only evaluate it based on a single index but must be based on the whole and use the multi-index comprehensive evaluation method to make an overall evaluation and comparison, in order to conduct a more comprehensive evaluation [10]. Radar chart has been successfully applied in many fields such as financial performance evaluation, power quality evaluation, enterprise competitive advantage evaluation, teaching informatization evaluation, and teacher classroom teaching quality evaluation due to its simplicity and intuitiveness and the ability to compare multiple index variables at the same time [11].

Learning is the active construction of knowledge by learners. Learning status refers to the physical and psychological functional status of students in the learning situation, mainly including the status of brain wakefulness and concentration, emotional status, and physical function status. [9]. The strength of the online learning state is directly related to the quality of the learner's learning effect. Online learning is different from traditional learning methods. It

breaks the constraints of time and space, and teachers and students are separated from each other. Therefore, the evaluation method of online learning must be different from the evaluation method for traditional teaching methods. The online learning state includes not only the learning preparation state before students engage in learning activities but also the learning psychological state and learning environment state of students engaged in learning activities and also includes the learning achievement state after students engage in learning activities [12]. The online learning state evaluation index system of literature [13] mainly selects the learning state of students engaged in learning activities, which can be evaluated from five indicators: attention state, human-computer interaction state, emotional state, social network state, and cognitive state. Attention is the direction and concentration of mental activities on a certain object and is a common psychological feature accompanied by psychological processes such as perception, memory, thinking, and imagination. Attention state is the measure of this direction and concentration; the computer interaction state is a measure of the degree of interaction between online learners and online learning platforms, such as login frequency, online time, and click rate. [14]; the emotional state refers to the emotional experience of learners in the learning process, such as happiness, pain, curiosity, interest, and boredom; the social network status refers specifically to learners' behaviors such as communication, discussion, interaction, and collaboration with teachers and other learners in the online learning community. For example, teacher-student interaction in the teaching process can be the data of questioning rate and feedback rate, student response rate, and active questioning rate that are analyzed [15]; and cognitive state refers specifically to the learner's understanding and mastery of knowledge and skills.

The key to optimizing the evaluation effect lies in the evaluation criteria of students' participation status, and all the value judgments made by teachers need to be carried out according to this. The process of formulating evaluation standards also reflects the teaching philosophy of teachers. Therefore, in the process of reconstructing the dynamic evaluation standards, it is first necessary to comprehensively examine the growth of students in terms of intelligence and nonintelligence factors and the classroom status, so as to determine the specific content and design classroom participation that is consistent with multidimensional development based on core literacy. Evaluation scheme to optimize the evaluation effect [16].

In the past, the focus of teaching evaluation has always been teacher-centered. The focus of everyone's attention is how to improve the quality of teaching from the perspective of teachers. However, not enough attention has been paid to the student's participation in teaching activities and their effects. According to the modern teaching concept, the center of classroom teaching should be student-centered and everything should be for students. We not only pay attention to whether the teacher's lectures are in place but also pay attention to the learning status of students in the whole learning process. The study of the learning status is of great help for students to establish a correct learning concept, correct learning attitude, improve methods, improve learning efficiency, and avoid academic failure. As a teacher, they can also provide timely help and guidance according to the student's learning status. In addition, the advancement of this work will have a profound impact on the work of college students, teaching work, curriculum reform and even teaching management [17].

College students have different majors and different needs for English. Only the liberal arts can be divided into office English, business English, legal English, financial English, and many other categories. Professional English cannot exist as an independent language. They are specialized subjects under the English language. Different professional English must have commonalities in the English language. This requires us to stick to the basic skills of the language, master the basic grammar and vocabulary, and have a certain ability for language expression. The foundation of basic English directly affects students' learning of professional English [18].

In order to improve the effectiveness of the evaluation of student's learning status in foreign language classrooms, this paper applies machine vision to classroom teaching, evaluates students' classroom status through intelligent feature recognition, and improves the evaluation effect of students' learning status.

### 2. Feature Tracking of the Students' Learning Status

2.1. Automatic Window Tracking Motion Strategy for the Machine Vision System Automatic Window Tracking Motion Algorithm of the Machine Vision System Based on Preset Visual Field Parameters. The marker point at the end of classroom feature recognition must be as close to the end of the microdevice as possible, so as to ensure that the motion information of the marker point can be obtained centrally within the window of the machine vision system, and its position has a variety of options. As shown in the kinematic coordinate system of the end link of the classroom feature recognition in the figure, in the forward kinematic model of the end of the classroom feature recognition, since the wrist of the microdevice has 3 degrees of freedom, the motion trajectory curve of the origin  $O_{10}^{in}$  of the end tool coordinate system is too complicated (including 6 active degrees of freedom), which is not conducive to the extraction of key information. However, the motion trajectory curve of the origin  $O_8^{in}$  of the pitch joint coordinate system of the microdevice is relatively greatly simplified (in essence, it contains 3 useful degrees of freedom), so it is the best choice for identifying the end marker points as classroom features.

Obtaining the trajectory of the marker point  $O_8^{\rm in}$  is mainly divided into the following steps: first, on the basis of the known pose of the coordinate system of the end tool for the recognition of two classroom features, the motion amount of each active joint is calculated through the inverse kinematics solution of the end of the classroom feature recognition, and the forward and inverse kinematics modeling of the end of the classroom feature recognition is carried out. Second, the motion amount  $\theta_4^{\text{in}}$ ,  $\theta_5^{\text{in}}$ ,  $\theta_6^{\text{in}}$ ,  $d_8^{\text{in}}$  of the first four active joints is substituted into the positive kinematics solution of the marker point, and as shown in formula (1), the pose matrix  $_{\text{in}}T_{N0}^8$  of the marker points A and B at the end 1 and 2 of the classroom feature recognition in the global coordinate system can be obtained. Finally, the position vector is extracted from the positive solution of the marked point, so as to obtain the movement trajectory  $in^{\lambda}P_{N0}^8$  of the marked point, as shown in formula (2).

$${}^{\lambda}_{in} T^{8}_{N0} = {}^{\lambda}_{in} T^{4}_{N0} \cdot_{in} T^{5}_{4} \cdot_{in} T^{5}_{5} \cdot_{in} T^{7}_{6} \cdot_{in} T^{8}_{7}$$

$$= \begin{bmatrix} {}^{\lambda}_{in} n_{x} & {}^{\lambda}_{in} O_{x} & {}^{\lambda}_{in} a_{x} & i_{in} p_{x} \\ {}^{\lambda}_{in} n_{y} & i_{in} O_{y} & i_{in} a_{y} & i_{in} p_{y} \\ {}^{\lambda}_{in} n_{z} & i_{in} O_{z} & {}^{\lambda}_{in} a_{z} & {}^{\lambda}_{in} p_{z} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$${}^{\lambda}_{in} P^{8}_{N0} = \begin{bmatrix} {}^{\lambda}_{in} p_{x} & {}^{\lambda}_{in} p_{y} & {}^{\lambda}_{in} p_{z} \end{bmatrix}^{T}.$$
(1)

When  $\lambda = 1$ , the position vector  ${}_{in} P^8_{N0}$  represents the marker point A at the end 1 of class feature recognition. When  $\lambda = 2$ , the position vector  ${}_{in} {}^2 \mathbf{P}^8_{N0}$  represents the marker point B at the end 1 of class feature recognition. After knowing the position vector of the marker point and the center point of the end of the machine vision system, the field of view parameters can be calculated.

The window replacement of the window tracking algorithm of the machine vision system can be divided into four processes, as shown in Figure 1. (1) Initial alignment refers to controlling the origin  $L_R$  of the end tool of the machine vision system to move from the initial position to the initial debugging point L<sub>s</sub> after the preoperative positioning of the dobby system is completed, so as to ensure that the center of the window coincides with the midpoint E of the marked points A and B. (2) Window adjustment refers to the process in which the desired teaching window is obtained by controlling the freedom of movement of the machine vision system arm and the zoom ratio of the window after the initial alignment is completed. (3) The current window means that the obtained machine vision system window is defined as the initial window after the window adjustment is completed. (4) The target window refers to the movement of the marker points A and B at the end of classroom feature recognition during the teaching operation, which will cause the change of the basic visual field parameter  $\xi$ . By establishing a tracking motion algorithm, the machine vision system arm is automatically guided to adjust the end point position, thereby ensuring the invariance of  $\xi$  and obtaining the target window. (5) The dynamic replacement process between the current window and the target window also realizes that the window of the machine vision system autonomously tracks the movement of the end marker point of classroom feature recognition and ensures the stability of the basic visual field parameter  $\xi$ . Thus, the operator's desired field of view of the window is always maintained. The autonomous tracking movement of the window is essentially a fine-tuning process of the center of the window.



FIGURE 1: Schematic diagram of the window replacement process of the window tracking algorithm of the machine vision system.

As shown in Figure 1,  $\gamma$  is the superwide angle of view of the machine vision system, and points  $C_0$  and  $D_0$  are the projection points of the marked points  $A_0$  and  $B_0$  on the plane  $\alpha$ , respectively. The coordinate system  $x_{E_0}y_{E_0}z_{E_0}$  at point  $E_0$  moves up along the centerline of the machine vision system, which can coincide with the visual coordinate system  $x_{L_s}y_{L_s}z_{L_s}$ ,  $x_{L_0}y_{L_0}z_{L_0}$ ,  $x_{L_a}y_{L_a}z_{L_a}$ ,  $x_{L_b}y_{L_b}z_{L_b}$  of the window, and the plane  $\alpha$  coincides with the coordinate system plane  $x_{E_0}y_{E_0}$ . The position vector of the marker points  $A_0$ and  $B_0$  in the global coordinate system  $X_0Y_0Z_0$  can be calculated according to the movement trajectory of the end tool system based on the classroom characteristics and is set as follows:

$$\begin{cases} P_{A_0} = \left[ x_{A_0} y_{A_0} z_{A_0} \right]^T, \\ P_{B_0} = \left[ x_{B_0} y_{B_0} z_{B_0} \right]^T. \end{cases}$$
(3)

It can be known that the position vector of the point  $E_0$  is as follows:

$$P_{E_0} = \frac{1}{2} \left( P_{A_0} + P_{B_0} \right). \tag{4}$$

From the initial positioning information and the forward kinematics of the machine vision system, it can be known that the position vectors of the telecentric fixed point  $M_L$ and the endpoint  $L_R$  of the machine vision system are as follows:

$$\begin{cases} P_{M_L} = \left[ x_{M_L} y_{M_L} z_{M_L} \right]^T, \\ P_{L_R} = \left[ x_{L_R} y_{L_R} z_{L_R} \right]^T. \end{cases}$$
(5)

The expectation is  $\|\overline{M_L L_R}\| = \|\overline{M_L L_s}\|$  in the initial alignment session. According to the principle of three-point collinearity, the L<sub>s</sub> position vector can be solved by (6) and used as the desired position of the machine vision system arm, so as to complete the initial alignment adjustment.

$$\overline{M_L L_S} = \frac{\overline{M_L E_0}}{\left\| \overline{M_L E_0} \right\|} \cdot \left\| \overline{M_L L_R} \right\|.$$
(6)

When the position vector of the point  $E_0$  is substituted into the inverse kinematics solution of the machine vision system arm, and the positive kinematics solution is input at the joint angle, the pose matrix of the point  $E_0$  in the global base system  $X_0Y_0Z_0$  at the end of the machine vision system can be calculated. It is set to be  $T_{E_0}$ , and its position vector and attitude matrix are  $P_{E_0}$  and  $R_{E_0}$ , respectively.

$$T_{E_0} = \begin{bmatrix} R_{E_0} P_{E_0} \\ 0_{1 \times 3} 1 \end{bmatrix}.$$
 (7)

In the formula,

$$\begin{cases}
P_{E_0} = \begin{bmatrix} x_{E_0} y_{E_0} z_{E_0} \end{bmatrix}^T, \\
R_{E_0} = \begin{bmatrix} E_0 n_x E_0 o_x E_0 a_x \\
E_0 n_y E_0 o_y E_0 a_y \\
E_0 n_z E_0 o_z E_0 a_z \end{bmatrix}.
\end{cases}$$
(8)

Then, it can be known that the position vectors of the marker points  $A_0$  and  $B_0$  in the window center coordinate system  $x_{E_0}y_{E_0}z_{E_0}$  can be calculated by the following formula.

In the formula,

$$\begin{cases} P_{A_0}^{E_0} = \left[ x_{A_0}^{E_0} y_{A_0}^{E_0} z_{A_0}^{E_0} \right]^T, \\ P_{B_0}^{E_0} = \left[ x_{B_0}^{E_0} y_{B_0}^{E_0} z_{B_0}^{E_0} \right]^T. \end{cases}$$
(9)

Obviously, the position vectors of points  $C_0$  and  $D_0$  in the coordinate system  $x_{E_0}y_{E_0}z_{E_0}$  of the center of the view-point are as follows:

$$\begin{cases} P_{C_0}^{E_0} = \left[ x_{C_0}^{E_0} y_{C_0}^{E_0} 0 \right]^T, \\ P_{D_0}^{E_0} = \left[ x_{D_0}^{E_0} y_{D_0}^{E_0} 0 \right]^T. \end{cases}$$
(10)

The position vector of the endpoint  $L_0$  of the machine vision system in the window adjustment in Figure 1 is as follows:

$$P_{L_0} = \left[ x_{L_0} y_{L_0} z_{L_0} \right]^T.$$
(11)

It can be known from the simultaneous equations (10)-(12) that in the window center coordinate system  $x_{E_0}y_{E_0}z_{E_0}$ , the vectors  $\overrightarrow{C_0D_0}$  and  $\overrightarrow{L_0E_0}$  are as follows:

$$\begin{cases} \overline{C_0 D_0} = P_{D_0}^{E_0} - P_{C_0}^{E_0}, \\ \overline{L_0 E_0} = P_{E_0} - P_{L_0}. \end{cases}$$
(12)

Then, the basic visual field parameter  $\xi = \angle C_0 L_0 D_0$  of the window is as follows:

$$\xi = 2 \times \tan^{-1} \frac{1}{2} \left( \left\| \overline{C_0 D_0} \right\| / \left\| \overline{L_0 E_0} \right\| \right).$$
(13)

Then, the basic visual field parameter  $\xi = \angle C_0 L_0 D_0$  of the window is as follows:

$$\xi = 2 \times \tan^{-1} \frac{1}{2} \left( \left\| \overline{C_0 D_0} \right\| / \left\| \overline{L_0 E_0} \right\| \right).$$
(14)

In the process of initial window adjustment, by adjusting the intervention length of the machine vision system along the line of sight of the machine vision system, the size of the basic field of view parameter angle can be changed. Similarly, the sizes of  $\xi_a$  and  $\xi_b$  during the adjustment process can be known as follows:

$$\begin{cases} \xi_a = \angle C_0 L_a D_0 = 2 \times \tan^{-1} \frac{1}{2} \left( \left\| \overrightarrow{C_0 D_0} \right\| / \left\| \overrightarrow{L_a E_0} \right\| \right), \\ \xi_b = \angle C_0 L_b D_0 = 2 \times \tan^{-1} \frac{1}{2} \left( \left\| \overrightarrow{C_0 D_0} \right\| / \left\| \overrightarrow{L_b E_0} \right\| \right), \end{cases}$$
(15)  
$$\xi_1 = 2 \times \tan^{-1} \frac{1}{2} \left( \left\| \overrightarrow{C_1 D_1} \right\| / \left\| \overrightarrow{L_1 E_1} \right\| \right).$$

The position vectors of the target markers  $A_2$  and  $B_2$  in the global base system  $X_0Y_0Z_0$  can be obtained as follows:

$$\begin{cases} P_{A_2} = \left[ x_{A_2} y_{A_2} y_{A_2} \right]^T, \\ P_{B_2} = \left[ x_{B_2} y_{B_2} y_{B_2} \right]^T. \end{cases}$$
(16)

The midpoint  $E_2$  of the marked points  $A_2$  and  $B_2$  is as follows:

$$P_{E_2} = \frac{1}{2} \left( P_{A_2} + P_{B_2} \right) = \left[ x_{E_2} y_{E_2} z_{E_2} \right]^T.$$
(17)

Points  $C_2$  and  $D_2$  are the projection points of the marked points  $A_2$  and  $B_2$  in the coordinate system  $x_{E_2}y_{E_2}z_{E_2}$  of the center of the window, and the plane  $\beta$  coincides with the plane  $x_{E_2}y_{E_2}$  of the coordinate system. In the same way, the projection of the vector  $\overline{C_2D_2}$  in the coordinate system  $x_{E_2}y_{E_2}z_{E_2}$  can be obtained.

$$\left\| \overline{L_2 E_2} \right\| = \frac{1}{2 \times \tan\left(\xi/2\right)} \left\| \overline{C_2 D_2} \right\|.$$
(18)

Combining formulas (5) and (17), it can be known that the vector  $\overrightarrow{M_LE_2}$  is as follows:

$$\overrightarrow{M_L E_2} = \left[ \left( x_{E_2} - x_{M_L} \right) \left( y_{E_2} - y_{M_L} \right) \left( z_{E_2} - z_{M_L} \right) \right]^T.$$
(19)

Then, it can be known that the vector  $\overrightarrow{L_2E_2}$  can be obtained by the following formula:

$$\overrightarrow{L_2E_2} = \left\| \overrightarrow{L_2E_2} \right\| \cdot \frac{\overrightarrow{M_LE_2}}{\left\| \overrightarrow{M_LE_2} \right\|}.$$
(20)

It is set to as follows:

$$\overrightarrow{L_2E_2} = \left[ x_{L_2E_2} y_{L_2E_2} z_{L_2E_2} \right]^T.$$
(21)

Then, the target position vector of the endpoint  $L_2$  of the machine vision system is as follows:

$$P_{L_2} = \left[ \left( x_{E_2} - x_{L_2 E_2} \right) \left( y_{E_2} - y_{L_2 E_2} \right) \left( z_{E_2} - z_{L_2 E_2} \right) \right]^T.$$
(22)

In Figure 1, point F is the end point of the trocar tube through which the machine vision system passes. The endpoint L of the machine vision system cannot be retracted into the trocar tube in the algorithm and point F is the retraction limit point of point L. The distance between the endpoint F of the trocar tube and the telecentric fixed point is  $l_F$ ; then, the vector  $\overline{M_L F}$  can be obtained by the following formula:





FIGURE 3: Marker movement track and endpoint tracking track.



FIGURE 4: Marker motion trajectories obtained using the Phantom master hand and endpoint tracking trajectories based on the machine vision system.

$$\overrightarrow{M_LF} = l_F \cdot \frac{\overrightarrow{M_LE_2}}{\left\| \overrightarrow{M_LE_2} \right\|} = \left[ x_{M_LF} y_{M_LF} z_{M_LF} \right]^T.$$
(23)

Then, the position vector of point F in the global base system is as follows:

$$P_{F} = \left[ \left( x_{M_{L}} - x_{M_{L}F} \right) \left( y_{M_{L}} - y_{M_{L}F} \right) \left( z_{M_{L}} - z_{M_{L}F} \right) \right]^{T}.$$
 (24)

The derivation process of the above formula shows that after adjusting and obtaining the basic visual field parameter  $\xi$ , the origin L of the visual coordinate system at the end of the

machine vision system tracks the movement of the marker points A and B at the end of the classroom feature recognition, and ensures the stability of the  $\xi$  value at all times.

## 3. Student Status Evaluation System

This paper combines the intelligent student status recognition algorithm based on machine vision proposed in the second part to construct a student status evaluation system based on machine vision, and the system is shown in Figure 2.



FIGURE 5: Movement speed of marker trajectories 1-4.

As can be seen from the figure, the realization of the recognition of student's classroom behavior includes three steps: dataset construction, algorithm model training, and student classroom behavior recognition. The first is dataset construction. Five types of behavioral states of students, such as raising hands, sleeping, answering, writing, and listening to lectures, were marked. The student behavior dataset is then trained with a substantially improved algorithm. During the training process, the input student behavior state pictures are forwarded to the SSD network for feature extraction. The candidate boxes of different prediction layers are matched with the ground-truth boxes, and the error of each candidate box category confidence prediction and position offset prediction is output. At the same time, the corresponding weights are adjusted by backpropagation of the calculated loss until the loss function drops to a small stable value, and the model training is completed. Finally, the identification of students' classroom behavior status is carried out. When the video frame to be detected is input into the smart classroom recording and broadcasting system, a series of detection frames are generated on the image frame through the trained parameter model. Through

non-maximum suppression, redundant boxes are eliminated, the best position box for detecting student behavior is obtained, and the five types of student behavior states of raising hands, sleeping, answering, writing, and listening are recognized.

In order to verify the correctness of the window tracking motion algorithm of the machine vision system, within the range of the motion space of the marker point at the end of the classroom feature recognition, based on the sine and cosine function, the marker point motion trajectory 1 obtained by formula (25) is planned, which is shown in Figure 2(a), and the marker point motion trajectory 2 obtained by formula (26), which is shown in Figure 2(b).

$$\begin{cases} x_{As} = 21 \sin(t) + 310, \\ y_{As} = 26 \cos(t) + 290, \\ z_{AS} = 20 \sin(2t) + 860, \end{cases} \begin{cases} x_{Bs} = -25 \cos(t) + 360, \\ y_{Bs} = 25 \sin(t) + 300, \\ z_{Bs} = 20 \cos(2t) + 870. \end{cases}$$
(25)

In the formula, the unit of position trajectory is  $mm, t \in [0, \pi/2]s$ , which represents the movement time of the planned trajectory, and the basic visual field parameter obtained by an adjustment is set to  $\xi = 37.6583$ deg.



FIGURE 6: The result of the kinematic inverse solution of the end tracking trajectory based on the machine vision system.

$$\begin{cases} x_{Ac} = 15 \sin(2t) + \cos(t) + 5 \sin(5t) + 330, \\ y_{Ac} = 18 \cos(t) + 3 \sin(4t) + 290, \\ z_{Ac} = 10 \sin(3t) + 13 \cos(t) + 900, \\ \{x_{Bc} = 18 \sin(2t) + 3 \cos(5t) + 300, \\ y_{Bc} = 17 \cos(t) + 6 \sin(5t) + 320, \\ z_{Bc} = 20 \cos(3t) + 3 \sin(t) + 900. \end{cases}$$
(26)

In the formula, the unit of the position trajectory is  $mm, t \in [0, 2\pi]s$ , which also represents the movement time of the planned trajectory, and the adjusted basic field of view parameter is set to  $\xi = 37.6531$  deg.

Using the PhantomOmni, master hand can obtain a marker trajectory that is closer to the teaching operation,

and the sampling period is set to 10 ms. On the basis of compensating for the absolute base position, the 1:1 incremental master-slave mapping method is used to simulate the motion trajectories 3 and 4 of the marker points at the end of classroom feature recognition, as shown in Figures 3 and 4. Since the "filtering algorithm" is not used to eliminate the jitter of the master hand trajectory, there is a high-frequency noise signal of the original operation jitter in the trajectory. At the same time, it is also equivalent to adding interference noise in the simulation, which is beneficial to check the basic performance of the motion algorithm.

On the basis of the initial adjustment and setting of the basic field of view parameters  $\xi$ , the trajectory curve of the origin (endpoint L) of the visual coordinate system of the machine vision system can be calculated. The velocity curves of the movement trajectories 1–4 of the marked points A and



FIGURE 7: The result of the window angle judgment condition of the end tracking trajectory based on the machine vision system.

B are shown in Figure 4. The maximum speeds of tracks 1–4 are 55 mm/s, 80 mm/s, 40 mm/s, and 110 mm/s, respectively, and the minimum speeds are 25 mm/s, 5 mm/s, 0 mm/s, and 0 mm/s, respectively. It can be seen that the mark point trajectory used in the simulation is a very difficult operation curve in actual teaching. At the same time, trajectories 3 and 4 are not filtered, and the velocity curve contains the influence of high-frequency noise, which is of great practical significance to verifying the correctness and feasibility of the window tracking algorithm.

In order to verify the correctness and feasibility of the window tracking algorithm, the simulation trajectories

shown in Figures 3 and 4 need to meet two conditions. (1) The end-tracking trajectory of the machine vision system is used as the expected motion curve, and the kinematic inverse solution of the arm of the machine vision system is input, and the obtained motion amount  $\theta_5^{la}$ ,  $\theta_6^{la}$ ,  $d_8^{la}$  of the active joint must be within the joint motion range, that is, the "kinematic inverse solution judgment condition" is satisfied. (2) The geometric relationship between the marker point A, B and the tracking point L in the target window as shown in Figure 1 must meet the following window angle determination conditions: the ultrawide angle of 0° is  $\gamma =$ 

TABLE 1: The evaluation effect of the system on the students' learning status in foreign language classrooms.

Number	Recognition effect	Number	Recognition effect	Number	Recognition effect
1	87.77	18	84.51	35	86.01
2	88.03	19	89.44	36	87.85
3	88.14	20	84.69	37	84.01
4	84.71	21	91.09	38	85.20
5	85.24	22	88.52	39	84.27
6	90.67	23	91.47	40	91.22
7	87.94	24	87.65	41	87.26
8	91.82	25	84.56	42	90.69
9	88.79	26	86.42	43	91.79
10	89.17	27	91.13	44	84.87
11	86.69	28	91.80	45	88.24
12	84.04	29	88.06	46	88.39
13	87.33	30	86.77	47	86.87
14	85.77	31	90.95	48	88.96
15	89.96	32	85.99	49	86.63
16	91.16	33	85.92	50	90.77
17	87.24	34	91.62	51	86.38

110deg,  $\angle A_2 L_2 B_2 < \gamma$ ,  $\angle A_2 L_2 E_2 < 0.5\gamma$ ,  $\angle E_2 L_2 B_2 < 0.5\gamma$ ,  $\angle A_2 L_2 B_2 < 90$ deg,  $\angle A_2 L_2 E_2 < 45$ deg,  $\angle E_2 L_2 B_2 < 45$ deg, and the basic field of view parameter  $\xi = \angle C_2 L_2 D_2$  remains the same as the initial adjustment setting value. The movement speed of the marker point trajectory 1–4 is shown in Figure 5.

Figures 6 and 7 show the verification results of the simulation trajectories 1–4 applying the kinematic inverse solution judgment conditions and the window angle judgment conditions. It can be seen that the inverse solutions of the active joints of the arm of the machine vision system are all within the motion range, and the window angle value and basic field of view parameters both meet the judgment conditions, thus verifying the correctness and feasibility of the window tracking motion algorithm.

The abovementioned research study verifies that the algorithm based on machine vision proposed in this paper can have a good application foundation in the evaluation of students' status in foreign language classrooms. On this basis, through multiple sets of simulation experiments, this paper explores the accuracy of the student state evaluation system based on machine vision. The results of the student learning status evaluation shown in Table 1 are obtained.

From the abovementioned research, it can be seen that the algorithm based on machine vision proposed in this paper can effectively judge the real-time status of students in the classroom and has an important auxiliary role for teachers to make teaching plans in a timely manner.

#### 4. Conclusion

In the foreign language classroom teaching environment, the recognition of students' facial expressions is helpful to know the students' learning status in time. With the deepening of students' facial expression recognition research, more and more researchers realize that high-quality facial expression database plays an important role in training effective recognition models and accurately understanding students' learning behaviors and states. So far, scholars at home and abroad have established many databases related to student expressions, but their construction standards and methods are not uniform. In addition, expression classification, as the core problem of expression recognition and the primary task of building an expression library, has not been well solved. In order to improve the effectiveness of the evaluation of student's learning status in foreign language classrooms, this paper applies machine vision to classroom teaching and evaluates students' classroom status through intelligent feature recognition. The research results show that the algorithm based on machine vision proposed in this paper can effectively judge the real-time status of students in the classroom.

#### **Data Availability**

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

#### **Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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