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Retraction

Retracted: Application of Speech Interaction System Model Based on Semantic Search in English MOOC Teaching System

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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

[1] B. Pan and Y. Zhou, "Application of Speech Interaction System Model Based on Semantic Search in English MOOC Teaching System," *Advances in Multimedia*, vol. 2022, Article ID 3557256, 12 pages, 2022.

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Research Article

Application of Speech Interaction System Model Based on Semantic Search in English MOOC Teaching System

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In order to improve the effect of English MOOC teaching, this study combines the semantic search algorithm to construct an English MOOC teaching system to promote the interactive effect of English teaching. Moreover, this study analyzes a DOA estimation method based on sparse iterative covariance and an improved method, and no prior knowledge of noise is required to use this method in noisy data scenarios. In addition, this study constructs an English interactive teaching system based on semantic search. Finally, this study uses the course resources of the MOOC platform to teach students, perform organizational collaboration, and answer the questions. The research shows that the speech interaction system model based on semantic search proposed in this study has a better application effect in the English MOOC teaching system.

1. Introduction

In the traditional mode of listening to lectures, the lecturers go to the lectures with notebooks. It is difficult to say that it is a structured scientific observation. It lacks a predetermined purpose, the meticulous division of labor, and effective observation techniques. The listener is more like an audience and is basically in a passive position. Therefore, we need a scientific and efficient way to listen to the class in class.

The connotation of classroom development is defined as three dimensions, which refer to the three specific aspects of knowledge and skills, process and method, emotional attitude, and values. In the teaching process, the three dimensions complement each other and cannot be separated from each other. At present, from the perspective of three-dimensional goals, knowledge and skills are the foundation, and without this foundation, the process will be impossible. Moreover, the process and method play a role in linking the previous and the next, and are the link between the other two dimensions. The understanding of this dimension of "process and method" in this study is that in the teaching process, teachers should not only teach students knowledge but also teach how to acquire knowledge [1]. Moreover, students must have the ability to discover problems, analyze problems and then solve them, fully embodying the teaching idea of "giving them fish is worse than teaching them to fish." In this general trend, we need to improve the original teacher evaluation method, which is relatively subjective. If there is no objective basis, the class will only be evaluated according to the general rules. In the past, listening to the class evaluation has become a formality, which only has a great impact on the teaching teachers [2]. However, it has little effect on the teachers attending the class. Obviously, the implementation of the new curriculum reform requires us to train teachers more professionally. "We are growing" is not only for the overall development of students but also for the professional growth of teachers. At the same time, curriculum reform requires the professional growth of teachers, which provides a broader stage for this [3].

As a scientific research method, classroom observation is different from other theories. First is the purpose. Purposefulness plays an important role in classroom observation, from pre-class meetings to after-class discussions, and it can not be separated from the observation point. These observation points are our observation purpose [4]. The second is systemic. Classroom observation should formulate a feasible observation strategy according to its own purpose, and make a scale according to science, and observe according to the scale, which makes the observation more systematic and scientific. The third is theoretical. Any research is inseparable from theory and scientific guidance. Both the formulation of the classroom observation scale and the evaluation mechanism of classroom observation need the guidance of classroom observation theory. Leaving the theory, classroom observation becomes a pure meaning of watching [5]. The fourth is optionality. Selectivity is a meaningful activity, among many observation points, we choose valuable observations to observe. The fifth is situational. Situationalism mainly refers to the observation that the observer is best at the scene, and if the video observation is used instead, the effect is not as good as that of the scene observation [6].

Classroom teaching is the so-called "class." And this class process is only an important component of classroom teaching. Classroom teaching includes lesson preparation, class, assignment, stage test, and other links. It is an important and main part of students' school life. It is a dynamic system composed of multiple complex relationships embodied by the interaction of multiple elements [7]. In classroom teaching, it mainly includes the following aspects: teaching design, commonly known as lesson plan, is the most important operation for teachers in lesson preparation. In the design, it is necessary to understand the curriculum standards and curriculum objectives in order to design a good lesson. Classroom teaching behavior refers to all aspects of the teacher's teaching in the classroom, including the teacher's control of the classroom and the degree of grasp of the students. Classroom teaching evaluation [8]. This mainly refers to the teacher's reflection on the classroom process, mainly whether the expected effect has been achieved, and what are the shortcomings of the teaching. Chemistry classroom teaching, as can be seen from the meaning of the word, is an act of imparting chemical knowledge, so the chemistry classroom is an application of classroom teaching in chemistry classroom, and it has become a kind of curriculum. Now, the curriculum teaching objectives in many areas are not simply one-dimensional objectives, but are derived from the perspective of chemistry courses on students' ability training [9].

Observational assessments based on assessment criteria are time-consuming and many principals are not confident enough to perform this time-intensive teacher assessment. Therefore, although each region emphasizes the importance of classroom observation and evaluation, because principals cannot complete teachers' classroom observation and evaluation, they will naturally not believe in and adopt this time-consuming evaluation model. Furthermore, the validity and reliability of criteria-based classroom observation assessments need to be based on effective training of observers [10]. Therefore, it is particularly necessary to reconsider who is responsible for teacher evaluation in the new classroom observation evaluation system. To think about this, it is key to distinguish between the shortcomings of the individual evaluator and the limitations of the evaluation system. Some principals may be unsuitable for evaluating classroom assignments, while others are better at it. Therefore, in the new reform of classroom observation and evaluation in the United States, the leadership role of education administrators is affirmed, and it is believed that teacher evaluation should also be led by principals. Although principals or other managers cannot evaluate and support all teachers, they can support expert teachers to go directly to teachers' classrooms to observe teachers' classrooms [11]. This reflects the shift of instructional leadership from individual instructional leadership to distributed instructional leadership, which mainly relies on leadership around the leader, expanding the extension of instructional leadership. This kind of teacher evaluation with the help of specialized observers brings benefits in at least two ways. First, observers can match it to their teaching subject [12]. Especially with the implementation of state common core standards, common evaluation criteria are becoming less tenable. Due to the complexity and particularity of teaching practice, different grades and different subject areas require different observers. Only by giving full play to the important value of the subject knowledge and subject teaching knowledge of professional observers can they help teachers to improve their practice and teaching in a targeted manner. Make sound judgments about the quality of practice [13]. Second, a large number of studies have proved that principals lack time, and time is the basic component of improving teaching quality through observation and evaluation. Therefore, principals are often limited by time and cannot really invest in teacher evaluation. They usually cannot find time to Completing observations and recording observations, a dedicated observer can devote more time to observing and evaluating than a principal who is in charge of the school as a whole, and can also devote the necessary time to professional learning to effectively diagnose a teacher's classroom performance And provide timely feedback [14]. Therefore, in the new classroom observation evaluation system in the United States, the classroom observation evaluation is performed by professional classroom observation evaluators, and the professional classroom observers are mainly composed of expert teachers in various subject areas [15].

Classroom observation refers to the method of recording, analyzing, and researching classroom implementation through observation. The purpose is to improve students' classroom learning status, ensure the effective implementation of teachers' professional activities, and achieve teachers' professional development. Different from observation in the ordinary sense, classroom observation is a research method, which requires observers to clarify the purpose of observation. In addition to using their own eyes and mind, they also need to use certain observation tools, such as classroom observation scales, recording equipment, etc., so as to collect data directly from the classroom, and make an effective evaluation of the classroom based on the data [16]. Class observation mainly consists of three stages: pre-class meeting, in-class observation, and after-class reflection. This is a systematic workflow from problem identification to information gathering to problem-solving.

Therefore, the content of the classroom observation scale mainly includes the following aspects: teachers' teaching methods, implementation of teaching objectives, questioning skills, teachers' control ability, students' initiative, students' cognitive performance, students' actual thinking performance, classroom atmosphere And students' study habits, etc. [17]. According to the main content of the classroom observation scale, it can be concluded that there are two main methods of classroom observation: qualitative method and quantitative method. You can focus on observing relatively important issues in the classroom, or you can focus on observing the performance of different teachers in the same class. Classroom observation requires the formulation of observation outlines, the recording of classroom observation objects, and finally analysis according to certain methods [18].

In order to improve the effect of English MOOC teaching, this study combines the semantic search algorithm to construct an English MOOC teaching system, which can promote the interactive effect of English teaching and improve the evaluation quality of English teaching.

2. Semantic Signal Search Algorithms

2.1. SPICE (SParse Iterative Covariance-Based Estimation Approach) Model. This method is suitable for uniform speech signal arrays and sparse linear arrays. The specific array model has been described in detail and will not be repeated here. We assume that there are K signal sources in the space. Considering the actual array processing scenario, the main problem is to estimate the location parameters of multiple narrowband signal sources present in the data received by the array. Moreover, we assume that Q represents the set of possible positions, and we also assume that O is the general position parameter. $\{\theta_k\}_k^K = 1$ denote the grid covering Ω. In addition, we assume that the grid is fine enough so that the true location of the resulting data is on (or close to) the divided grid. Under these reasonable assumptions, the received array data can be represented using the following nonparametric model:

$$y(t) = \sum_{k=1}^{K} a_k s_k(t) + \varepsilon(t), \quad t = 1, 2, \ldots, M\,(N \times 1). \tag{1}$$

In the formula, M is the total number of snapshots, N is the number of elements in the array, K is the number of voice sources, $y(t) \in C^{N\times 1}$ is the t-th snapshot, a_k is the array flow pattern, $s_k(t)$ is the unknown signal from the source at θ_k, and $\varepsilon(t)$ is the noise term.

Sparse (or semi-parametric) estimation methods are reminiscent of the assumption of parametric methods that only a small number of signal sources are present. Therefore, some rows of the signal matrix are nonzero.

$$S = \begin{bmatrix} s_1(1) & \cdots & \cdots & s_1(M) \\ \vdots & \vdots & \vdots & \vdots \\ s_K(1) & \cdots & \cdots & s_K(M) \end{bmatrix}. \tag{2}$$

In the array data $\{y(t)\}$, the rows of the matrix in formula (2) are nonzero. The description of the speech source location problem requires the use of basic ideas in the field of sparse parameter estimation, and these ideas are simply extended to the current multi-snapshot situation. To describe these ideas concisely, they are expressed in the form of formulas (3)–(5).

$$Y^H = [y(1), \ldots, y(M)] \in C^{N\times M}, \tag{3}$$

$$S = \begin{bmatrix} S_1^H \\ \vdots \\ S_K^H \end{bmatrix} \in C^{K\times M}, \tag{4}$$

$$B^H = [a_1, \ldots, a_K] \in C^{N\times K}. \tag{5}$$

Among them, $[\bullet]^H$ represents the conjugate transpose, B represents the steering vector matrix, and the usual steering vector representation A is used as a reserved symbol, which will be used in the next section. Directly applying the L1 norm minimization principle, the models described by formulas (1) to (5) are used to estimate the signal matrix S, which can be transformed into the solution of the following minimization constraint problem:

$$\min_S \sum_{k=1}^{K} \|s_k\| \ \mathrm{s \cdot t \cdot} \ \|Y^H - B^H S\| \le \eta. \tag{6}$$

In the formula, $\|\bullet\|$ represents the Euclidean norm of the vector and the Frobenius norm of the matrix, and n is a specific threshold selected. Note that the target in formula (6) is equal to the L1 norm of the vector $\{\|s_k\|\}_k^K = 1$.

2.2. SPICE Fitting Criterion. The key of the sparse iterative method based on covariance fitting is to fit the observed covariance matrix obtained from the data received from the finite snapshot array to the real covariance matrix corresponding to the actual infinite snapshot data. To implement this process, some assumptions are made first.

$$E[\varepsilon(t)\varepsilon^*(t)] = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sigma_N \end{bmatrix} \delta_{t,\bar{t}}. \tag{7}$$

In the above formula, $E[\bullet]$ is the expected lift, and $\delta_{t,\bar{t}} = \begin{cases} 1, \text{if } t = \bar{t} \\ 0, \text{elsewhere} \end{cases}$. The noise term added in formula (1) is completely reasonable in practical application scenarios. It is also assumed that the signal $\{s_k(t)\}$ and the noise $\varepsilon(\bar{t})$ are not correlated at any time. Therefore, we can get the following equation:

$$E\left[s_k(t) s_{\bar{k}}^H(\bar{t})\right] = p_k \delta_{k,\bar{k}} \delta_{t,\bar{t}}. \tag{8}$$

At the same time, we assume that the snapshot data $\{y(1), \ldots, y(M)\}$ are not correlated with each other, then we have the covariance matrix of the following formula:

$$\begin{aligned}
R &= E\left[y(t)y^H(t)\right] \\
&= \sum_{k=1}^{K} p_k a_k a_k^H + \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sigma_N \end{bmatrix} \\
&= [a_1, \ldots, a_K, I] = \begin{bmatrix} p_1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & p_2 & 0 & \cdots & \cdots & \cdots & 0 \\ \vdots & 0 & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & p_k & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \sigma_1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \sigma_N \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_K \\ I \end{bmatrix} \\
&\triangleq A^H P A.
\end{aligned} \tag{9}$$

In formula (9), p_k is the eigenvalue corresponding to the signal, σ is the eigenvalue corresponding to the noise, and the identity matrix I represents the steering vector of the noise. In formula (9), we can get

$$\begin{aligned}
A^H &\triangleq [a_1, \ldots, a_K, I] \\
&\triangleq [a_1, \ldots, a_K, a_{K+1}, \ldots, a_{K+N}], \\
P &\triangleq \begin{bmatrix} p_1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & p_2 & 0 & \cdots & \cdots & \cdots & 0 \\ \vdots & 0 & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & p_K & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \sigma_1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \sigma_N \end{bmatrix} \\
&\triangleq \begin{bmatrix} p_1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & p_2 & 0 & \cdots & \cdots & \cdots & 0 \\ \vdots & 0 & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & p_K & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & p_{K+1} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \cdots & \cdots & \cdots & p_{K+N} \end{bmatrix}.
\end{aligned} \tag{10}$$

We assume that the signals are spatially uncorrelated and thus have a representation of the covariance of formula (9). However, in some scenarios, the signals are correlated or even coherent, so the expression of formula (9) does not necessarily hold, but the SPICE method is robust to this.

To proceed with DOA parameter estimation, the covariance fit criterion of formula (11) is now considered.

$$f = \left\| R^{-(1/2)} (\widehat{R} - R) \widehat{R}^{-(1/2)} \right\|_F^2. \tag{11}$$

In formula (11), R represents the observation covariance matrix, which is specifically expressed as $R = Y$ “Y/M, and R represents the true covariance matrix of the signal. Moreover, it is assumed that the inverse of R and R exists. In fact, although the "true" values of many eigenvalues in R may be zero, the covariance matrix R mentioned here is usually nonsingular when the noise eigenvalues are greater than zero. Regarding the estimated covariance matrix R, the inverse of this matrix is consistent with the probability that the true covariance is nonsingular when the number of snapshots is greater than the number of elements.

When the number of snapshots is less than the number of array elements, that is, when $M < N$, the covariance matrix of the sample data is nonsingular, then formula (11) cannot be used, and the following estimation criteria will be used:

$$f = \left\| R^{-(1/2)} (\widehat{R} - R) \right\|_F^2. \tag{12}$$

Among them, for the sake of simplicity, only considering the actual common situation that the number of snapshots is greater than the number of array elements, and formula (11) is simplified. Taking advantage of matrix knowledge, the square of the F-norm of a matrix is equal to the trace of the product of the matrix's conjugate transpose and itself.

$$\|A\|_F^2 = tr\left(A^H A\right). \tag{13}$$

From the knowledge of matrix theory, the trace of its self-conjugate transpose and self-product are equal. Using this knowledge, formula (11) can be simplified to

$$\begin{aligned}
f &= \left\| R^{-(1/2)} (\widehat{R} - R) \widehat{R}^{-(1/2)} \right\|^2 \\
&= tr\left[\widehat{R}^{-(1/2)} (\widehat{R} - R) \widehat{R}^{-(1/2)} R^{-(1/2)} (\widehat{R} - R) \widehat{R}^{-(1/2)}\right] \\
&= tr\left[R^{-1} (\widehat{R} - R) \widehat{R}^{-1} (\widehat{R} - R)\right] \\
&= tr\left[\left(R^{-1}\widehat{R} - I\right)\left(I - \widehat{R}^{-1} R\right)\right] \\
&= tr\left(R^{-1}\widehat{R}\right) + tr\left(\widehat{R}^{-1} R\right) - 2N.
\end{aligned} \tag{14}$$

In formula (14), R is the observation matrix covariance matrix, and R is the actual covariance matrix to be fitted. From the knowledge of matrix theory, the conclusion of formula (15) can be obtained.

$$tr\,(ab) = b^H a. \tag{15}$$

According to formula (15), the trace operation of formula (14) can be further simplified:

$$\begin{aligned}
tr\left(R^{-1}\widehat{R}\right) &= tr\left(\widehat{R}^{-1} \sum_{k=1}^{K+N} p_k a_k a_k^H\right) \\
&= tr\left(\sum_{k=1}^{K+N} p_k a_k \widehat{R}^{-1} a_k^H\right) \\
&= \sum_{k=1}^{K+N} p_k a_k^H \widehat{R}^{-1} a_k \\
&= \sum_{k=1}^{K+N} \left(a_k^H \widehat{R}^{-1} a_k\right) p_k.
\end{aligned} \tag{16}$$

From formulas (14) and (16), it can be obtained that the minimization of f is equivalent to the minimization of g as follows:

$$g = tr\left(R^{-(1/2)}R^{-1}\widehat{R}^{-(1/2)}\right) + \sum_{k=1}^{K+N}\left(a_k^H\widehat{R}^{-1}a_k\right)p_k. \tag{17}$$

Similarly, formula (12) can be simplified as

$$\begin{aligned} f &= \left\|R^{-(1/2)}(\widehat{R}-R)\right\|^2 \\ &= tr\left[(\widehat{R}-R)\widehat{R}^{-(1/2)}R^{-(1/2)}(\widehat{R}-R)\right] \\ &= tr\left[(\widehat{R}-R)\widehat{R}^{-1}(\widehat{R}-R)\right] \\ &= tr\left[\left(R\widehat{R}^{-1}-I\right)(\widehat{R}-R)\right] \\ &= tr\left(\widehat{R}R^{-1}\widehat{R}-2\widehat{R}+R\right). \end{aligned} \tag{18}$$

Since tr(2R) is a constant, the optimization cost function does not need to consider this term, it only needs to consider the following formula:

$$\begin{aligned} g_1 &= tr\left(\widehat{R}R^{-1}\widehat{R}+R\right) \\ &= tr\left(\widehat{R}R^{-1}\widehat{R}\right) + tr(R) \\ &= tr\left(\widehat{R}R^{-1}\widehat{R}\right) + tr\left(\sum_{k=1}^{K+N} p_k a_k a_k^H\right) \\ &= tr\left(\widehat{R}R^{-1}\widehat{R}\right) + \sum_{k=1}^{K+N} a_k^H a_k p_k \\ &= tr\left(\widehat{R}R^{-1}\widehat{R}\right) + \sum_{k=1}^{K+N} \left\|a_k\right\|^2 p_k. \end{aligned} \tag{19}$$

In formula (19), g represents the optimization cost function of (12). In formula (17), the minimization problem of $\{p\}$ can be easily formulated as a positive semi-definite programming (SDP) problem, so it is a convex problem. It follows from formula (17) that a consistent estimate on the right-hand side of the equation is given by the value of the number of array elements N. Therefore, it can be considered to redefine formula (18) as the following minimization constraint problem:

$$\min_{(p_k\geq 0)} tr\left(\widehat{R}^{1/2}R^{-1}\widehat{R}^{1/2}\right)\text{s.t.} + \sum_{k=1}^{K+N} w_k p_k = 1. \tag{20}$$

In formula (20), there is $w_k = a_k^H\widehat{R}^{-1}a_k/N$. As the number of snapshots M continues to increase, and under the condition that formula (10) can represent the real covariance matrix R, formulas (20) and (20) are completely equivalent, and their solutions are scaled versions of each other. (Because the scaling of $\{P\}$ has no effect on the position estimate of the signal source). It can be known that formula (20) is also a positive semi-definite programming problem, so it is a convex problem. Furthermore, note that the linear constraint in formula (20) is of the weighted L1 norm type. Therefore, it is obvious that the solution of (20) is sparse.

2.3. SPICE Fast Iterative Algorithm. Reconsidering formula (20), we first define $C \in C^{(K+N)\times N}$, and reconsider the following problem:

$$\min_{C} tr\left(C^H P^{-1} C\right)\text{S.t.}A^H C = \widehat{R}^{1/2}. \tag{21}$$

For a fixed value of P, the solution to formula (21) is

$$C_0 = PSR^{-1}\widehat{R}^{1/2}. \tag{22}$$

Furthermore, the minimum value of formula (21) is

$$tr\left(C_0^H P^{-1} C_0\right) = tr\left(\widehat{R}^{1/2}R^{-1}\widehat{R}^{1/2}\right). \tag{23}$$

The solution of (23) for this minimum is consistent with formula (20). To prove the above statement, formula (22) is observed, if it can be proved that X and Y are Hermitian matrices with appropriate dimensions, and X-Y, then their difference matrix X-Y is a positive semi-definite matrix.

$$C_0^H P^{-1} C \geq C_0^H P^{-1} C_0 = \widehat{R}^{1/2}R^{-1}\widehat{R}^{1/2}\text{s.t.}A^H C = \widehat{R}^{1/2}. \tag{24}$$

By the standard properties of the blocking matrix and the known condition $R > 0$ in this study, if and only if the following blocking matrix is positive and semi-positive timing:

$$\begin{aligned} \begin{bmatrix} C^H P^{-1} C & \widehat{R}^{1/2} \\ \widehat{R}^{1/2} & R \end{bmatrix} &= \begin{bmatrix} C^H P^{-1} C & C^H A \\ A^H C & A^H P A \end{bmatrix} \\ &= \begin{bmatrix} C^H & 0 \\ 0 & A^H \end{bmatrix}\begin{bmatrix} P^{-1} & I \\ I & P \end{bmatrix}\begin{bmatrix} C & 0 \\ 0 & A \end{bmatrix} \leq 0. \end{aligned} \tag{25}$$

The center matrix in formula (25) can be rewritten as

$$\begin{bmatrix} P^{-1} & I \\ I & P \end{bmatrix}\begin{bmatrix} P^{-(1/2)} \\ P^{1.2} \end{bmatrix}\left[P^{-(1/2)} \quad P^{1/2}\right]. \tag{26}$$

It can be seen from formula (26) that formula (25) is obviously positive and semi-definite. Because it has the form $X''X$, and has the form $X = \left[P^{-(1/2)} \quad P^{1/2}\right]$. It is thus proved that the minimum solution of formula (21) can be replaced by formula (23). In conclusion, this study has proved the above conclusion that for any fixed $P \geq 0$, the objective minimization expression for C in formula (21) yields exactly the original function of P in formula (20). Therefore, formula (21) has the same eigenvalues $\{p;\}$ as the minimization of formula (20) with respect to C and eigenvalues $\{p\}$.

The purpose of this transformation is that the minimization of the augmentation function in formula (21) can be accomplished more conveniently by a loop algorithm. The idea of the algorithm is to first minimize the formula (21) with respect to the variable C, then fix the value of P, and for a given C, minimize the formula (21) to obtain P, and repeat the cycle until convergence.

The first step of the algorithm has been derived, as in formula (22), and now the second step of the algorithm is given, for which we set as follows:

$$C = \left[c_1^H, \ldots, c_{K+N}^H\right]^T. \tag{27}$$

It can be observed that

$$tr\left(C^H P^{-1} C\right) = tr\left(P^{-1} C C^H\right) = \sum_{k=1}^{K+N} \frac{\left\|c_k\right\|^2}{p_k}. \tag{28}$$

In the implementation process, the implementation of the algorithm is different according to whether the noise eigenvalues are the same or not. The iterative algorithms for the two cases of different noise and the same noise are given respectively.

When the noise eigenvalue $\{\sigma_k\}$ is different, according to the Cauchy-Schwarz inequality, the following equation can be achieved:

$$\left[\sum_{k=1}^{K+N} w_k^{1/2}\left\|c_k\right\|\right]^2 \leq \left[\sum_{k=1}^{K+N} \frac{\left\|c_k\right\|^2}{p_k}\right]^2 \left[\sum_{k=1}^{K+N} w^k p_k\right] = \sum_{k=1}^{K+N} \frac{\left\|c_k\right\|^2}{p_k}. \tag{29}$$

It follows that the minimization of the objective of $\{pi\}$ in formula (21) is expressed as (for a fixed given value of C):

$$p_k = \frac{\left\|c_k\right\|}{w_k^{1/2}\rho}, \rho = \sum_{m=1}^{K+N} w_m^{1/2}\left\|c_m\right\|. \tag{30}$$

The corresponding minimum value for the target is

$$\left(\sum_{m=1}^{K+N} w_m^{1/2}\left\|c_m\right\|\right)^2. \tag{31}$$

The specific solution process of the second step of the loop algorithm is given by formula (30), and the solution process of the first step is given by formula (31). Combining formulas (30) and (31), the complete iterative formula of the SPICE iterative algorithm can be derived:

$$p_k^{i+1} = p_k^j \frac{\left\|a_k^H R^{-1}(i)\widehat{R}^{-(1/2)}\right\|}{w_m^{1/2}\rho(i)}, \quad k = 1, \ldots, K+N,$$
$$\rho(i) = \sum_{m=1}^{K+N} w_m^{1/2} p_m^j \left\|a_m^H R^{-1}(i)\widehat{R}^{-(1/2)}\right\|. \tag{32}$$

In the above formula, i represents the number of iterations, and the power initialization estimation of the algorithm can be obtained by the periodogram method:

$$p_k^0 = p_k^j \frac{a_k^H \widehat{R} a_k}{\left\|a_k\right\|^4}, \quad k = 1, \ldots, K+N. \tag{33}$$

In the case of the same noise eigenvalue $\{\sigma_k\}$, that is,

$$\sigma_1 = \cdots = \sigma_N \overset{\Delta}{=} \sigma. \tag{34}$$

In the above case, the formula (28) becomes the following formula:

$$tr\left(C^H P^{-1} C\right) = \sum_{k=1}^{K} \frac{\left\|c_k\right\|^2}{p_k} + \sum_{k=K+1}^{K+N} \frac{\left\|c_k\right\|}{\sigma}. \tag{35}$$

At the same time, the minimization of the function of formula (28) becomes

$$\sum_{k=1}^{K} w_k p_k + \gamma\sigma = 1. \tag{36}$$

In formula (36), we can get

$$\gamma = \sum_{k=K+1}^{K+N} w_k. \tag{37}$$

Similar to the situation when the noise eigenvalues are different, the specific process of the fast iterative algorithm at this time can be obtained as follows:

$$p_k = \frac{\left\|c_k\right\|}{w_k^{1/2}\rho}, \quad k = 1, \ldots, K, \tag{38}$$

$$p_k = \frac{\left\|c_k\right\|}{w_k^{1/2}\rho}, \quad k = 1, \ldots, K. \tag{39}$$

Among them, we can get the following formula:

$$p = \sum_{k=1}^{K} w_k^{1/2}\left\|c_k\right\| + \gamma^{1/2}\left[\sum_{k=K+1}^{K+N} w_k^{1/2}\left\|c_k\right\|^2\right]^{1/2}. \tag{40}$$

At this time, the minimization function for the case of fixing the value of C is

$$\left(\sum_{k=1}^{K} w_k^{1/2}\left\|c_k\right\| + \gamma^{1/2}\left[\sum_{k=K+1}^{K+N} w_k^{1/2}\left\|c_k\right\|^2\right]^{1/2}\right)^2. \tag{41}$$

So far, this study gives the specific steps of the iterative algorithm in the two cases of different noise eigenvalues and the same noise eigenvalues.

The initial solution obtained by inserting the constrained problem transformed by the fitting criteria into formulas (38) and (39) is formula (22). In the case of the same noise eigenvalues in formula (34), a modified SPICE iterative algorithm is proposed, which is called SPICE-plus (SPICE+), and the specific expression is as follows:

$$p_k^{i+1} = p_k^i \frac{\left\|a_K^H R^{-1}(i)\widehat{R}^{-(1/2)}\right\|}{w_k^{(1/2)}\rho(i)}, \quad k = 1, \ldots, K,$$

$$\sigma^{i+1} = \sigma^i \frac{\left\|R^i(i)\widehat{R}^{1/2}\right\|}{\gamma^{1/2}\rho(i)},$$

$$\rho(i) = \sum_{k=1}^{K} w_k^{1/2} p_k^i \left\|a_K^H R^{-1}(i)\widehat{R}^{-(1/2)}\right\| + \gamma^{1/2}\sigma^i\left\|R^{-1}(i)\widehat{R}^{-(1/2)}\right\|. \tag{42}$$

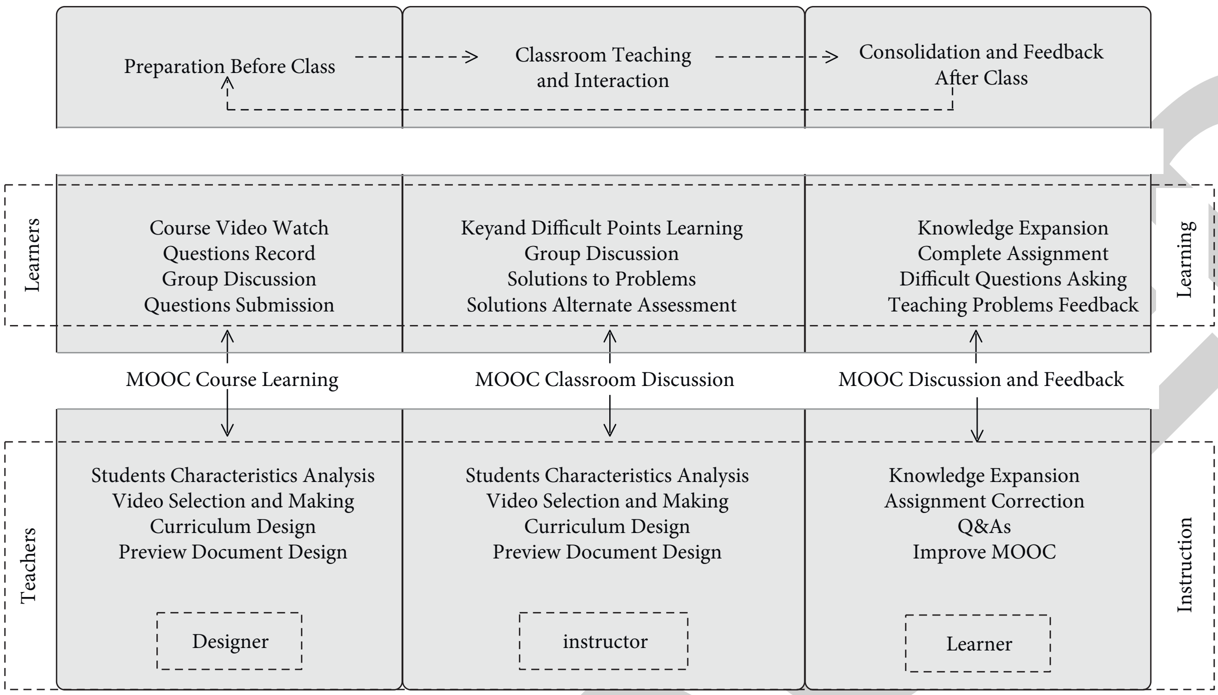

FIGURE 1: Curriculum teaching framework.

Similarly, the initial estimate of power can still be obtained using the periodogram, as in formula (33). In addition, o can be initialized as the mean of the N smallest values of $\{p_k^0\}_k^K = 1$ times $\|a_k\|^2$.

Since the foregoing is based on the incoherent signal assumption, and since formula (22) is used in the iterative algorithm, it can be expected that in the incoherent case, SPICE+ has globally convergent properties because SPICE monotonically decreases the objective function (due to its cyclic operation) and because the minimization problem it solves is convex. This is indeed the case, according to the general analysis, it is proved that under weak conditions (basically requiring $p_k > 0$ and matrix $R(i)$ remains positive definite as the iteration proceeds), the solution of the iterative process of the SPICE algorithm is the global solution of formula (19).

2.4. English MOOC Teaching System Based on Semantic Search. Teachers use the curriculum resources of the MOOC platform to teach students and are responsible for organizing collaboration and answering questions during the process. When teachers have professional knowledge about modern optimization algorithms, even teachers who are engaged in the scientific research of modern optimization algorithms can quickly build a curriculum construction system, which greatly shortens the training cycle of teachers. At the same time, teachers can also use MOOC resources to quickly update teaching content, reducing the difficulty of course promotion. The teaching framework of modern optimization algorithm course based on MOOC is shown in Figure 1.

Teachers, students, and resources are the three main components of online courses. The operation mode of the system is a dynamic description of the whole process of teachers' teaching and students' learning, reflecting the relationship between the three components. Therefore, analyzing and designing the operating mode of the system is a macro grasp of the entire learning process, and is also the basis for improving the traditional LTSA framework and designing the system's functions. The system operation mode diagram in a complete cycle is shown in Figure 2.

Through the analysis of the data structure MOOC system operation mode and the summary of the characteristics, we have a clearer understanding of the learning process of learners and the teaching process of teachers, as well as the relationship between teachers, learners, and resources. The learner and the resource are not independent, and the two have a complementary relationship, as shown in Figure 3.

In this system, all kinds of information generated by learners in the learning process are collectively referred to as learner resources, and according to the learning process, the types of resources are divided into three time periods: before class, during class, and after class, as shown in Figure 4.

Most of these resources take the unit cycle as the life cycle. Before the next unit cycle starts, the resources in this unit cycle can not only be viewed, but also can be discussed. When the next unit cycle begins, learners can only access and evaluate resources. However, depending on the specific application environment, some resources can complete the deadline in advance. For example, in a question discussion, if the answer to a question is accepted, the question discussion ends, and the learner cannot participate in the discussion, but can only obtain relevant resources. After the resource life cycle is over, these initially extracted resources are called basic resources. Because of their large quantity and uneven resource value, a resource evaluation model is established, as shown in Figure 5.

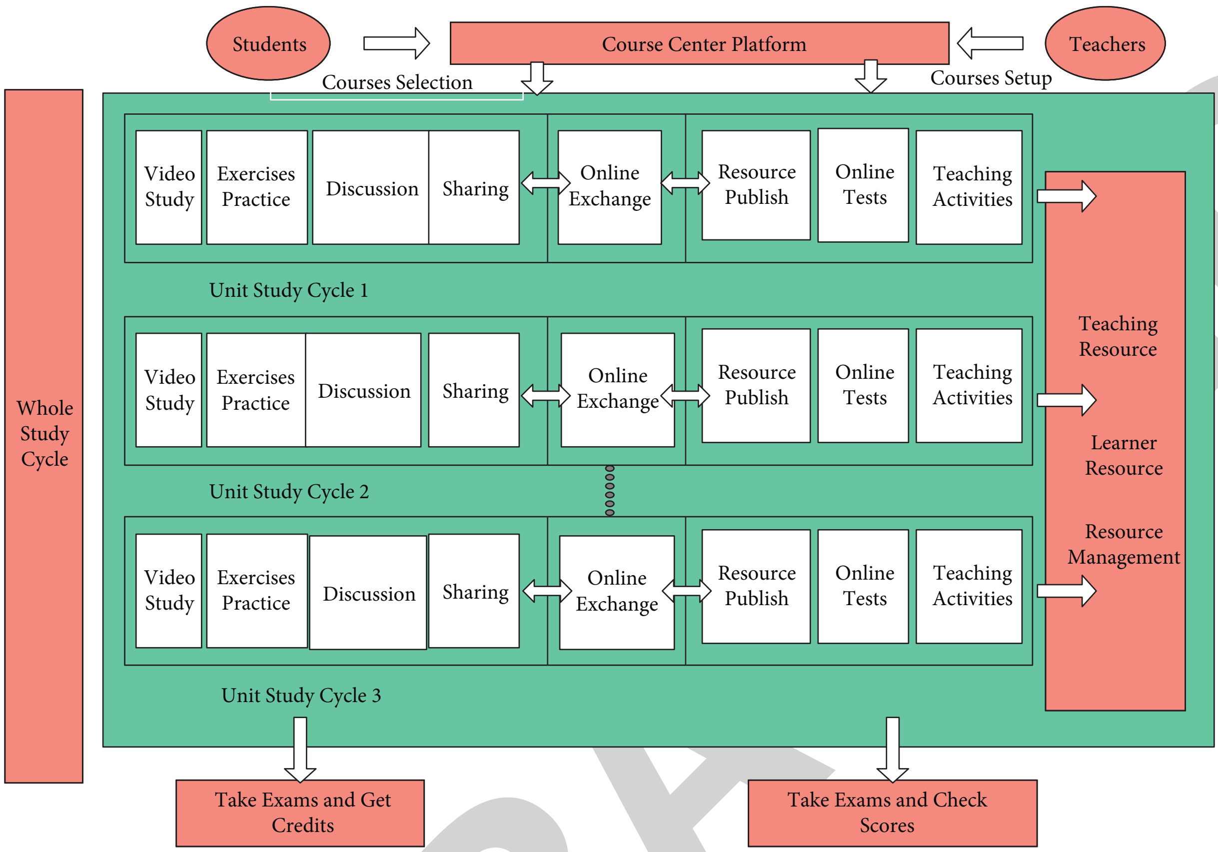

Figure 2: System operation mode diagram in a complete cycle.

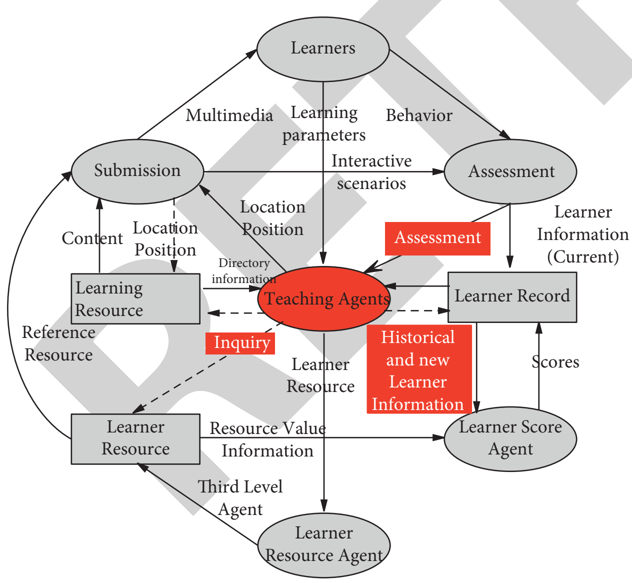

Figure 3: Data structure MOOC learning management framework.

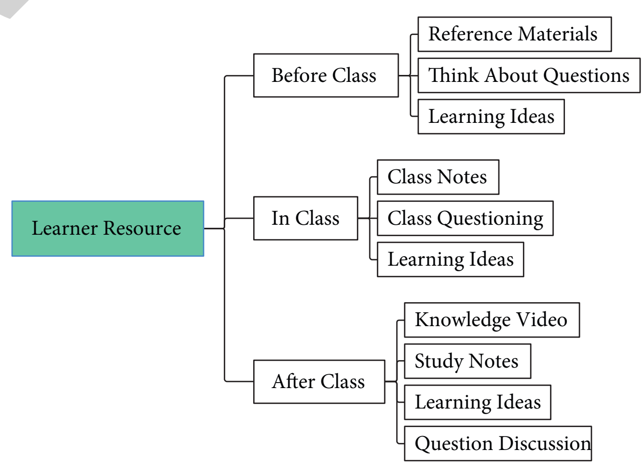

Figure 4: Composition diagram of learner resources.

The overall function of the data structure MOOC system mainly includes a course introduction module, a learner module, a teacher module and an administrator module, as shown in Figure 6.

The dynamic system includes three elements: learning motivation, learning goals, and learning feedback. Learning motivation is the basis for establishing learning goals, learning goals are the inherent requirements of learning motivation, and learning feedback runs through between learning motivation and learning goals. Through feedback evaluation of learning motivation and learning goals, learners' interest in learning can be better stimulated, and learners can be helped to adjust and optimize their goals according to the situation in the personalized learning process. The personalized learning system in the MOOC environment is shown in Figure 7.

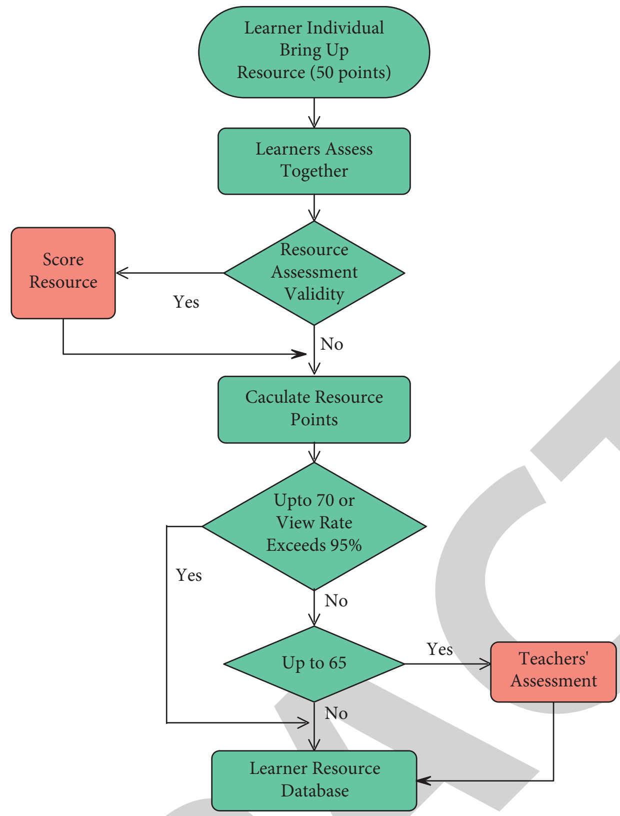

FIGURE 5: Flowchart of excellent resource evaluation.

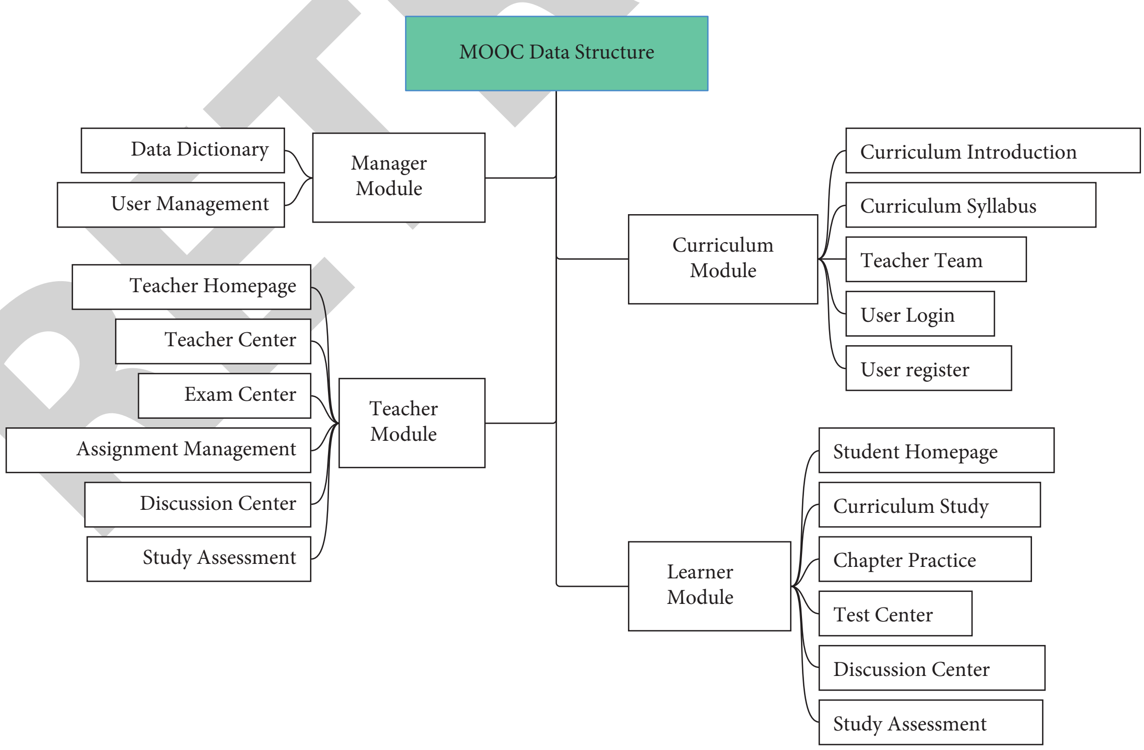

FIGURE 6: Overall functional design diagram of the system.

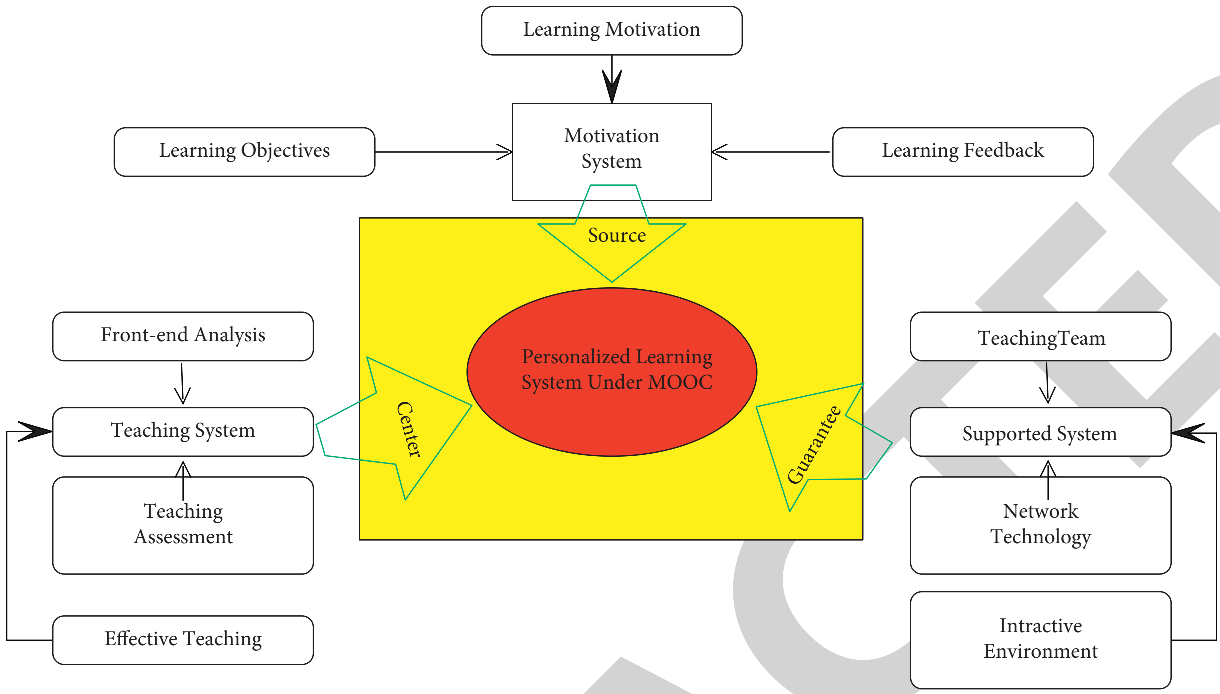

Figure 7: Personalized learning system in MOOC environment.

3. Simulation Test

A numerical simulation of the above method is carried out. The simulation uses a signal source with a fixed position. The voice signal array is a uniform voice signal array (ULA). The positions of the three sources are $\theta_1 = 10^\circ$, $\theta_2 = 30^\circ$, and $\theta_3 = 50^\circ$, and the three signals are $s_1(t) = 3e^{j\varphi 1(t)}$, $s_2(t) = 3e^{j\varphi 2(t)}$, and $s_3(t) = 3e^{j\varphi 3(t)}$, respectively. Among them, their phases $\{\varphi k(t)_k^0\}_{k=1}^3$ are independently distributed in the range of $[0, 2\pi]$. In coherent source simulation, 0 and 0, are coherent sources, so they have the same phase.

$$SNR = 10\log\left(\frac{100}{\sigma}\right) = 20 - \log\sigma[dB]. \tag{43}$$

In the comparative experiment, three methods are used for comparison, namely the MUSIC method, the SPICE method, and the SPICE+ method.

In the simulation experiment, the mean root mean square error (RMSE) of the DOA estimates obtained by 100 Monte Carlo experiments for the three methods under different signal-to-noise ratio conditions was simulated. The definition of RMSE is shown in

$$RMSE = \left[\frac{1}{300}\sum_{k=1}^{3}\sum_{m=1}^{100}\left(\theta_k^m - \theta_k\right)^2\right]. \tag{44}$$

In the above formula, θ_k^m is the estimation result of the mth Monte Carlo experiment of the kth signal. θ_k is the value set by the kth signal. The results of the numerical simulation are shown in Figure 8.

Figure 8 shows the RMSE results of the coherent source simulation. It can be seen from this that the DOA results of the IAA method are less accurate when the signal-to-noise

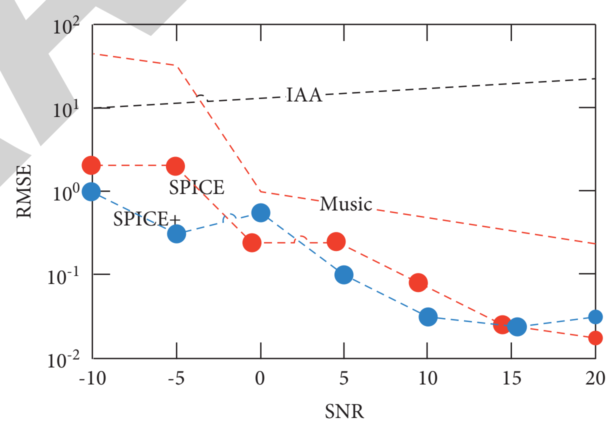

Figure 8: RMSE results with coherent sources.

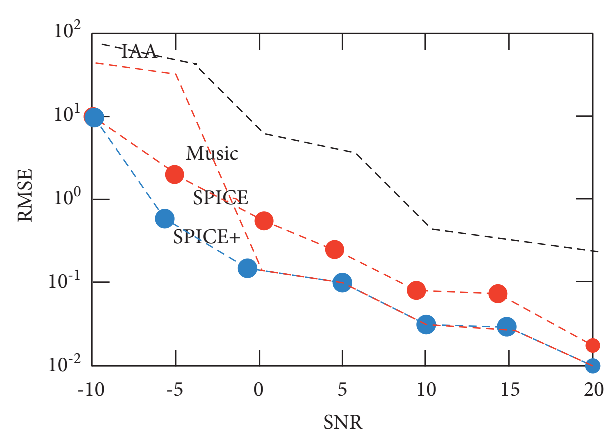

Figure 9: RMSE results with no coherent source.

Table 1: The application effect of the speech interaction system model based on semantic search in the English MOOC teaching system.

Number	Apply effects	Number	Apply effects	Number	Apply effects
1	81.85	18	87.36	35	86.14
2	81.27	19	83.73	36	85.53
3	83.92	20	79.80	37	84.55
4	85.45	21	87.93	38	86.31
5	80.99	22	84.97	39	86.38
6	87.32	23	83.89	40	85.41
7	87.28	24	82.41	41	85.04
8	85.57	25	84.31	42	86.22
9	80.83	26	84.58	43	80.76
10	79.00	27	80.49	44	82.80
11	83.84	28	84.31	45	79.69
12	84.93	29	79.21	46	79.68
13	85.25	30	81.06	47	81.41
14	82.30	31	79.54	48	86.15
15	79.79	32	82.83	49	81.39
16	85.68	33	81.69	50	80.95
17	85.17	34	87.32	51	84.62

ratio is low, that is to say, the IAA algorithm can only compete with other algorithms when the signal-to-noise ratio is greater than zero. Also, we know that the MUSIC method is a parametric method. Since it needs to know the number of signal sources in the data, in the case of incoherent sources, a very accurate DOA estimate can be made when the SNR is greater than zero for the SNR. The reason is that the MUSIC method is only valid for noncoherent signals, so in the coherent source test, the MUSIC results are completely wrong.

Figure 9 shows the RMSE results for incoherent sources. The SPICE algorithm and SPICE+ algorithm introduced in this chapter have a better performance for both situations. The detection threshold of the SPICE algorithm is about 10 dB lower than that of the IAA and MUSIC algorithms. For uncorrelated sources, SPICE+ performs better than SPICE. The reason is that the improvement of SPICE+ is to add the original solution of the minimization problem, and the minimization problem is proposed based on the condition of signal incoherence. However, SPICE performs better than SPICE+ in the case of coherent sources. From the results, it can be concluded that both algorithms are robust to coherent sources.

On this basis, the effect of the model proposed in this study is verified, and the simulation test results are shown in Table 1.

It can be seen from the above research that the speech interaction system model based on semantic search proposed in this study has a good application effect in the English MOOC teaching system.

4. Conclusion

As a form of online courses, MOOC has driven great changes and innovations in the field of education. However, in actual operation, many online courses have the problem of improper management of resources and learners, so there is a phenomenon of "teaching" but not "learning" or "teaching" but less "learning." Therefore, it is necessary to learn from the advanced ideas and practical application environment of MOOC. In view of the common problems in the current online courses, the design and implementation of a two-way interactive mode of teacher teaching and student learning system still needs continuous development and innovation, and it will also become the development trend of future online education. This study combines the semantic search algorithm to construct an English MOOC teaching system to promote the interactive effect of English teaching. The research results show that the research on the speech interaction system model based on semantic search proposed in this study has a better application effect in the English MOOC teaching system.

Data Availability

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

Conflicts of Interest

The authors declare no conflicts of interest.

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