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Computer Network Technology for College Students and its Application in English Interactive Teaching

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Abstract: In order to improve the interactive effect of English teaching, this paper constructs an interactive English teaching mode based on the computer network technology of information fusion and clustering. In addition, this paper applies computer network technology teaching simulation algorithm to English teaching interactive information processing, and proposes two online blind equalization algorithms for normal mode signals and multi-mode signals respectively. In these two algorithms, the cost function of the network is constructed using the prior statistics of the transmission signal, and the output weight of the network is solved iteratively using the recursive least squares algorithm (RLS). In order to prevent algorithm divergence, this paper proposes a dual-mode operation method and constructs an English interactive teaching system based on information technology and computer network technology. The experimental research shows that the interactive English teaching system based on information technology and computer network technology proposed in this paper can effectively improve the interactive effect of English teaching.

Keywords: college students; computer network technology; English; interactive teaching

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1 INTRODUCTION

In the traditional teaching view, teachers are the authority of classroom teaching, and teachers lead students in every step of teaching, and questioning is regarded as an important means to stimulate students' thinking and carry out heuristic teaching. Moreover, teachers' teaching lacks creativity, and students do not have a certain free thinking space, cannot carry out independent English activities, and do not have personal emotional experience. In the new teaching concept, teachers are the "leaders of equality", and in a democratic, equal and harmonious classroom atmosphere, teachers and students conduct two-way communication and interaction.

Student-to-student interaction is the interaction between individual individuals. Student-student interaction must be realized in a certain classroom teaching situation. Every student is a source of knowledge in classroom teaching activities. They have their own cognitive methods, their own choices, their own personality characteristics, and they have huge potential for development and development. Therefore, student-student interaction involves three classroom teaching situations of competition, individuality and cooperation. Among these three classroom teaching situations, the most important is the cooperative classroom teaching situation [12]. In the cooperative classroom teaching situation, to meet the needs of individual development and classroom interaction, let students experience the need to have the ability to make decisions that affect their peers, so that individuals can obtain higher self-esteem, social skills and psychological adjustment ability. It has been fully developed in the interaction [16].

To achieve effective English classroom interaction, teachers need to carefully design teaching situations, attract students' attention and enthusiasm for exploration, so that more students can participate in the process of learning new knowledge independently. Teacher-student interaction in the process of English classroom teaching must be achieved. Create interesting, useful, actionable, and explorable English situations. Let students take English learning as a fun, a kind of enjoyment, a kind of exploration and desire for the wonderland of English, and give students a pair of eyes to see the world with English eyes, and see a highly abstract phenomenon through the surface phenomenon of the real world. English-based scientific world, so that students can get good development [6].

Questions are the soul of the English classroom. The questions created by teachers should serve classroom interaction, be compact, concise, and targeted. The so-called "jump to pick the fruit", the setting of the question should be close to the students' existing knowledge and ability, the content of the question setting should be oriented towards most English students, it should not be too superficial or too deep, and it should be close to the actual situation of the students. Good question setting It can inspire thinking and make the classroom more exciting [4]. To grasp the difficulty of the problem, the most important thing is the connection between the problem design and classroom interaction. The problem must be closely connected with knowledge points and classroom interaction, and serve to solve difficult points. As a teacher, you must be good at summarizing difficult points. Arouse students' active participation and awareness of inquiry. When the problem is a little difficult, teachers can use clever language to guide, give students time and space to think, adjust teaching ideas in time when it is difficult, be good at flexibility, and focus on classroom interaction At difficult points, try to allow students to explore independently to gain knowledge and awareness, and to improve their own abilities [7].

Teachers should seize the opportunity to raise design questions in the classroom. For example, after discussing some problems, students still seem to understand but do not understand. At this time, they will have a deeper memory. This is a good time for teachers to guide and inspire. Seizing the opportunity, just right guidance can achieve twice the result with half the effort [8]. For difficult problems, designing gradient problems allows students to explore independently and gradually comprehend, which is more meaningful than teachers telling students the results directly. The problem can also be decomposed into small problems at different levels, from simple to easy, or for different students, to guide everyone to solve the problems encountered together, and effectively achieve teacher-student interaction [10].

The English classroom is no longer just the teacher's unilateral knowledge imparting, and the teaching interaction is no longer the teacher's one-man show.), or cleverly set up questions to make the classroom different [1]. In addition, teaching interaction is not only introduced in the classroom or occasional occasions, it occurs throughout the entire class. Teachers, as the executors, organizers, and guides of students' learning, should strengthen the training of basic teaching skills, improve their own teaching quality, participate more in students' learning and life, know themselves and others, and study teaching strategies from the perspective of students. Such teachers and students can Cooperate with each other to truly realize the interaction between teachers and students [3].

The interaction subjects have obvious gaps in knowledge, experience, and tasks. Teachers are much better than students in grasping subject courses. However, students have different cognitive styles and different personality characteristics from adults. Cognition and understanding of the world, at a certain point or aspect of its interest, may surpass teachers, especially in the information age, students in terms of information acquisition methods, speed, quantity, etc. [17]. Problems that teachers think are simple may become difficult problems for some students; problems that teachers think can be ignored and can be ignored by students may be very interesting to students, which requires teachers to stand with students from the perspective of students rather than adults. To carry out the contrastive interaction of equality and democracy, teachers should be soberly aware of this point in education and teaching [14].

The new curriculum advocates the interaction between teachers and students, so that teaching is no longer a one-way knowledge instruction, but an enlightening interaction of "process and method", "emotional attitude and value". The point of interaction between teachers and students is not only knowledge, but also the procedures, methods, strategies, emotional experience, value awareness, etc. to acquire knowledge [11]; the interaction between teachers and students is not only about students actively questioning, asking, asking and showing themselves to teachers The quality of learning is also based on the learning situation of students, teachers can either induce ideas, stimulate interest, or point to ways, or help reflect, or give examples, or guide comprehension. In a word, the teacher as an interactive party focuses on inspiring thinking and mobilizing students' internal motivation, so that students can learn to actively acquire knowledge and acquire skills independently [13].

Students are the main body of learning activities. In classroom teaching, the teaching idea of "students as the main body and teachers as the leading" must be established; the time arrangement and organizational form must fully reflect the students as the main body, and fully realize the teacher's role in the role. In teaching design, students must discover problems, make breakthroughs in difficult problems, let students summarize the method, and let students participate in evaluation, fully mobilize students' initiative and enthusiasm for learning, and create conditions for students to achieve their dominant position [2]]. In the teaching process, teachers can only implement their leading role in the active learning of students, reflect the students' main body status, become the active object of learning, the master of learning, coupled with the teacher's own rich knowledge, and use the teaching skills freely , students will have a strong interest in learning, from "I want to learn" to "I want to learn", they will feel the endless fun of learning [15].

In successful classroom teaching, the interaction between teachers and students is generated between teachers and students and between students by means of exploring, asking questions, and solving doubts. In the process of interaction, sparks of wisdom can often be generated. It is difficult to appear in the classroom, only in an atmosphere of harmony, democracy, equality and friendship can it be nurtured and multiplied [9]. Therefore, the teacher-student relationship is another important factor in the effectiveness of teacher-student interaction. Teachers should actively communicate with students, establish a new teacher-student relationship of equality and cooperation, and create a harmonious and democratic classroom atmosphere. In the teaching interaction, especially respect and care for the self-esteem of the students, must not be bruised at will, not only restrain those who are complacent, but also motivate those with low self-esteem, teachers must be good at regulating their attitudes, emotions and behaviors [5].

This paper constructs an interactive English teaching mode based on the computer network technology of information fusion and clustering, and studies the effect of its teaching practice after constructing the mode, which effectively improves the quality of English interactive teaching.

2 TEACHING SIMULATION ALGORITHM BASED ON COMPUTER NETWORK TECHNOLOGY

2.1 Online Blind Equalization Algorithm for Normal Mode Signals

In the echo state network, the input weight W_{m} and the state weight W_{res} of the teaching simulation system are randomly generated and kept unchanged, and the only parameter that needs to be trained is the output weight W_{out} of the network. Therefore, combined with the traditional blind equalization method based on cost function, the online blind equalization algorithm is used to iteratively optimize the output weights of the network, and the online blind equalization based on ESN can be realized. At this time, the ESN is used as the equalizer of the whole blind equalization system, the received signal x(n) is the input of the network at time n, and it is input into the dynamic teaching simulation system through the input layer. The sparse connection of the teaching simulation system is nonlinearly mapped to the state $\mathrm{u}(n)$ of the teaching simulation system at time n, which is read out through the output layer, and the online blind equalization algorithm is used to iteratively optimize the output weights. Its algorithm principle is shown in Figure 1.

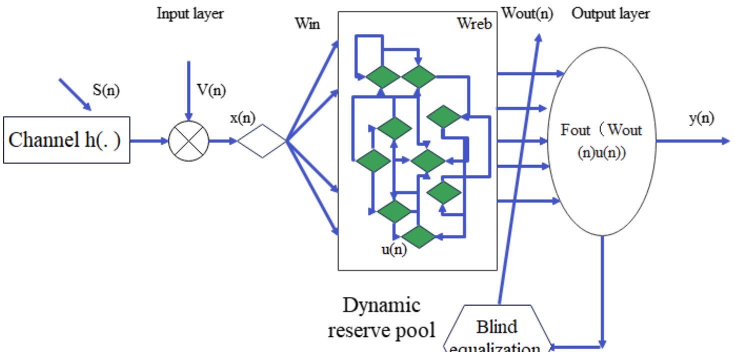


Figure 1: Basic principle diagram of online blind equalization algorithm based on ESN.

In order to iteratively update the output weight W_{out} of ESN online and speed up the iterative convergence speed of the network, the RLS algorithm is used to solve the minimum value of the cost function. Since the algorithm is recursive in time, time variables are also introduced into the network output weight vector and error vector. For the normal mode signal, the signal statistic $R_{CMA}=E\left[|s(n)|^4\right]/E\left[|s(n)|^2\right]$ in the normal mode algorithm (CMA) is substituted into the ESN to construct the blind equalization cost function, as shown in formula (2.1):

$$J(n)=\sum_{k=1}^{n}\lambda^{n-k}\left|R_{CMA}-\left|y(k,n)\right|^2\right|^2=\sum_{k=1}^{n}\lambda^{n-k}\,|e(k)|^2 \tag{2.1}$$

Among them, $0<\lambda\leq 1$ is the forgetting factor. To simplify the structure, if the output layer readout function of ESN is $f_{out}(\cdot)=1$, then there is $y(k,n)=\mathrm{W}_{out}(n)\mathrm{u}(k)$. Among them, $\mathrm{W}_{out}(n)$ is the weight vector of the ESN output layer at time n, $\mathrm{u}(k)$ is the state of the teaching simulation system at time $k(k=1,2,...,n)$, y(k,n) is the re-estimation of the output signal of the ESN at time k in the past, and e(k) is the estimation error at time k.

To make the cost function satisfy the standard quadratic form required by the RLS algorithm, we define:

$$\mathrm{U}(k,n)=\mathrm{u}(k)\left(\mathrm{W}_{out}(n)\mathrm{u}(k)\right)^{*} \tag{2.2}$$

Among them, "*" represents the conjugate of the matrix, then formula (2.1) can be written as:

$$J(n)=\sum_{k=1}^{n}\lambda^{n-k}\left|R_{CMA}-\mathrm{W}_{out}(n)\mathrm{U}(k,n)\right|^{2} \tag{2.3}$$

$\mathrm{U}(k,n)$ can be approximated as:

$$\mathrm{U}(k,n)\approx\mathrm{U}(k,n)=\mathrm{u}(k)\left(\mathrm{W}_{out}(n-1)\mathrm{u}(k)\right)^{*} \tag{2.4}$$

If the algorithm converges, then there must be:

$$\lim_{n\to\infty}\left\|\mathrm{W}_{out}(n)-\mathrm{W}_{out}(n-1)\right\|=0 \tag{2.5}$$

Therefore, $\mathrm{U}(k,n)$ can be used to approximate $\mathrm{U}(k,n)$. Therefore, formula (2.3) can be rewritten as:

$$J(n)=\sum_{k=1}^{n}\lambda^{n-k}\left|R_{CMA}-\mathrm{W}_{out}(n)\mathrm{U}(k,n)\right|^{2} \tag{2.6}$$

The gradient of the exponential cost function (2.6) can be expressed as:

$$\nabla J(n)=\mathrm{R}(n)\mathrm{W}_{out}(n)-\mathrm{r}(n) \tag{2.7}$$

Among them, $\mathrm{R}(n)=\sum_{k=1}^{n}\lambda^{n-k}\mathrm{U}(k,n)\mathrm{U}^{H}(k,n)$ is the autocorrelation matrix and $\mathrm{r}(n)=\sum_{k=1}^{n}\lambda^{n-k}\mathrm{U}(k,n)R_{CMA}$ is the cross-correlation vector.

According to the optimal solution $\nabla J(n)=0$ of the least squares optimization problem, we can get:

$$\mathrm{W}_{out}(n)=\mathrm{R}^{-1}(n)\mathrm{r}(n) \tag{2.8}$$

Formula (2.8) can be solved by time recursion. Since the update of $\mathrm{W}_{out}(n)$ is time recursive, $\mathrm{R}(n)$ and $\mathrm{r}(n)$ need to be estimated recursively according to the exponential sliding window. Through the matrix inversion lemma, we can get:

The recursive formula of the autocorrelation inverse matrix $\mathrm{P}(n)=\mathrm{R}^{-1}(n)$ is:

$$\mathrm{P}(n)=\frac{1}{\lambda}\left[\mathrm{P}(n-1)-\mathrm{k}(n)\mathrm{U}^{H}(n,n)\mathrm{P}(n-1)\right] \tag{2.9}$$

Among them, $\mathrm{k}(n)=\dfrac{\mathrm{P}(n-1)\mathrm{U}(n,n)}{\lambda+\mathrm{U}^{H}(n,n)\mathrm{P}(n-1)\mathrm{U}(n,n)}$ is the gain vector, also known as the Kalman increment. "H" represents the conjugate transpose of the matrix.

When formula (2.9) is substituted into formula (2.8), the recursive formula of ESN output weight W_{out} is obtained:

$$\mathrm{W}_{out}(n)=\mathrm{W}_{out}(n-1)+\mathrm{k}(n)e^{*}(n) \tag{2.10}$$

Among them,

$$e(n)=R_{CMA}-\mathrm{W}_{out}(n-1)\mathrm{U}(n,n) \tag{2.11}$$

is the prior estimation error.

In addition, the forgetting factor λ has a great influence on the algorithm performance of RLS. The larger the λ, the higher the convergence accuracy of the algorithm, but at the same time, the convergence speed will be slower, and the perception of signal changes will be smaller. On the contrary, the smaller λ is, the faster the algorithm converges, but the convergence accuracy will be reduced. The literature presents a method to adaptively adjust the forgetting factor λ. The adjustment formula is

$$\lambda(n)=\lambda_{min}+\left(1-\lambda_{min}\right)2^{L(n)} \tag{2.12}$$

Among them, $L(n)=-\left[p(n)|e(n)|^{2}\right],p(n)=\dfrac{20\left(e^{|e(n)|}-1\right)}{1+e^{|e(n)|}},p(n)$ is the control function, which controls the rate of change of λ.

The blind equalization cost function constructed by the above algorithm satisfies the least squares criterion. It replaces the traditional pseudo-inverse process by the inversion lemma of the matrix to solve the optimal solution of the ESN output weight W_{out}. Moreover, the iterative solution process of recursive formula (10) satisfies the least squares criterion, so the above algorithm is convergent.

Online blind equalization algorithm for multimode signals

SN-RLS-CMA substitutes the error function in the traditional CMA into the ESN to construct the cost function, and uses the RLS algorithm to iteratively solve the output weight of the ESN. This algorithm can effectively solve the problem of blind equalization of normative signals. For multimode signals, ESN-RLS-CMA may have large equalization errors and cannot solve the phase ambiguity problem. The basic idea of multimode algorithm (MMA) processing complex signals is to separate the real and imaginary parts of the input signal and overcome the above problems by minimizing the equalizer output. This section draws on the basic idea of MMA processing multi-mode signals, constructs the cost function of blind equalization, and still uses the RLS algorithm to solve the optimal solution of the cost function. First, the blind equilibrium cost function is constructed as follows:

$$J(n)=(1-\lambda)\sum_{k=1}^{n}\lambda^{n-k}\left\{\left[R_{MMA}-y_R^2(k,n)\right]^2+\left[R_{MMA}-y_I^2(k,n)\right]^2\right\} \tag{2.13}$$

Among them, $0 \ll \lambda < 1$ is the forgetting factor, $R_{MMA}=E\left\{s_R^4(n)\right\}/E\left\{s_R^2(n)\right\}=E\left\{s_1^4(n)\right\}/E\left\{s_1^2(n)\right\}$ is the statistic of the original transmitted signal, $E\{\bullet\}$ is the mathematical expectation, S_R and S_I are the real and imaginary parts of the transmitted signal, and y_R and y_I are the real and imaginary parts of the ESN output signal, respectively. If $f_{out}(*)=1$, then there is:

$$y(k,n)=y_R(k,n)+jy_I(k,n)=\mathrm{W}_{out}(n)\mathrm{u}(k) \tag{2.14}$$

Similarly, according to the least squares optimal solution criterion, the cost function formula (2.13) calculates the gradient $\nabla J(n)$ for the output weight $\mathrm{W}_{out}(n)$ of the ESN, and $\nabla J(n)=0$ is set to obtain:

$$R_{MMA}\mathrm{R}(n)\mathrm{W}_{out}(n)=\mathrm{p}(n) \tag{2.15}$$

Among them,

$$\mathrm{R}(n)=\sum_{k=1}^{n}\lambda^{n-k}\mathrm{u}^*(k)\mathrm{u}^T(k)=\lambda\dot{\mathrm{R}}(n-1)+\mathrm{u}^*(n)\mathrm{u}^T(n) \tag{2.16}$$

$$\mathrm{p}(n)=\sum_{k=1}^{n}\lambda^{n-k}\left[y_R^3(k,n)+jy_I^3(k,n)\right]\mathrm{u}^*(k) \tag{2.17}$$

In order to obtain the time recursive formula of $\mathrm{W}_{out}(n)$, it can be known from formula (2.15) that the recursive equations of the autocorrelation matrix $\mathrm{R}(n)$ and the cross-correlation matrix $\mathrm{p}(n)$ need to be obtained first. The iterative error $\mathrm{W}_{out}(n)$ at time n is defined as:

$$\Delta\mathrm{W}_{out}(n)=\mathrm{W}_{out}(n)-\mathrm{W}_{out}(n-1) \tag{2.18}$$

From formulas (2.16) and (2.18), the recursive equation on the left side of the equal sign of formula (2.15) can be obtained as:

$$R_{MMA}\mathrm{R}(n)\mathrm{W}_{out}(n)=\lambda R_{MMA}\mathrm{R}(n-1)\mathrm{W}_{out}(n-1) + R_{MMA}\mathrm{R}(n)\Delta\mathrm{W}_{out}(n)+R_{MMA}y(n)\mathrm{u}^{*}(n) \tag{2.19}$$

Among them, $y(n)=y_R(n)+jy_I(n)=\mathrm{W}_{out}(n-1)\mathrm{u}(n)$.

Formulas (2.17) contains nonlinear terms. To obtain the approximate recursive equation of the cross-correlation matrix $\mathrm{p}(n)$, we define:

$$\Delta y_R^3(k,n)+j\Delta y_I^3(k,n)=\left[y_R^3(k,n)-y_R^3(k,n-1)\right] + j\left[y_I^3(k,n)-y_I^3(k,n-1)\right] \tag{2.20}$$

By substituting formula (2.20) into formula (2.17), we get:

$$\mathrm{p}(n)=\sum_{k=0}^{n}\lambda^{n-k}\left[y_R^3(k,n-1)+jy_I^3(k,n-1)\right]\mathrm{u}^{*}(k) + \sum_{k=0}^{n}\lambda^{n-k}\left[\Delta y_R^3(k,n)+j\Delta y_I^3(k,n)\right]\mathrm{u}^{*}(k) \tag{2.21}$$

The approximate expression for the second term on the right-hand side of formula (2.21) can be obtained from the following assumptions. Higher-order cumulants are defined:

$$\kappa_R=E\left\{y_R^3(n)\mathrm{u}^{*}(n)\right\}-3E\left\{y_R^2(n)\right\}E\left\{y_R(n)\mathrm{u}^{*}\right\} \tag{2.22}$$

$$\kappa_I=E\left\{y_I^3(n)\mathrm{u}^{*}(n)\right\}-3E\left\{y_I^2(n)\right\}E\left\{y_I(n)\mathrm{u}^{*}\right\} \tag{2.23}$$

In formulas (2.22) and (2.23), the empirical mean is usually used instead of the expected mean, then $E\left\{y_R^2(n)\right\}$ and $E\left\{y_I^2(n)\right\}$ can be replaced by $E\left\{s_R^2(n)\right\}=E\left\{s_I^2(n)\right\}$. When the output weight of the ESN at the previous moment is $\mathrm{W}_{out}(n-1)$, the complex vector $\kappa(n)=\kappa_R(n)+j\kappa_I(n)$ can be approximately replaced by:

$$\hat{\kappa}_{n-1}(n)=\sum_{k=1}^{n}\lambda^{n-k}\left[y_R^3(k,n-1)+jy_I^3(k,n-1)\right]\mathrm{u}^{*}(k)-3E\left\{s_R^2(n)\right\}\mathrm{R}(n)\mathrm{W}_{out}(n-1) \tag{2.24}$$

Similarly, when the output weight of the ESN is $\mathrm{W}_{out}(n)$, $\kappa(n)$ can be approximately replaced by:

$$\hat{\kappa}_{n}(n)=\sum_{k=1}^{n}\lambda^{n-k}\left[y_R^3(k,n)+jy_I^3(k,n)\right]\mathrm{u}^{*}(k)-3E\left\{s_R^2(n)\right\}\mathrm{R}(n)\mathrm{W}_{out}(n) \tag{2.25}$$

Because of $0 \ll \lambda < 1$, when n is large enough, $\hat{\kappa}_{n-1}(n)$ calculated from $W_{out}(n-1)$ is approximately equal to $\hat{\kappa}_n(n)$ calculated from $W_{out}(n)$, namely:

$$\kappa(n) \approx \hat{\kappa}_{n-1}(n) \approx \hat{\kappa}_n(n) \tag{2.26}$$

By formula (2.24), formula (2.25) and formula (2.26), we can get:

$$\sum_{k=1}^{n} \lambda^{n-k} \left[\Delta y_R^3(k,n) + j\Delta y_I^3(k,n) \right] \mathrm{u}^*(k) \approx 3E\left\{ s_R^2(n) \right\} \mathrm{R}(n)\Delta \mathrm{W}_{out}(n) \tag{2.27}$$

The approximate recursive equation for $\mathrm{p}(n)$ can be obtained by substituting formula (2.27) into formula (2.21):

$$\hat{\mathrm{p}}(n) = \lambda \hat{\mathrm{p}}(n-1) + \left[y_R^3(n) + jy_I^3(n) \right] \mathrm{u}^*(n) + 3E\left\{ s^2(n) \right\} \mathrm{R}(n)\Delta \mathrm{W}_{out}(n) \tag{2.28}$$

Through the above analysis, we obtain the recurrence equation of the ESN output weight

$$\mathrm{W}_{out}(n) = \mathrm{W}_{out}(n-1) + \frac{e(n)}{\gamma} \mathrm{R}^{-1}(n) \mathrm{u}^*(n) \tag{2.29}$$

Among them, the error $e(n) = e_R(n) + je_I(n) = \left[R_{MMA} - y_R^2(n) \right] y_R(n) + j\left[R_{MMA} - y_I^2(n) \right] y_I(n)$, $\gamma = 3E\left\{ s_R^2(n) \right\} - R_{MMA}$. The inverse $\mathrm{R}^{-1}(n)$ of the autocorrelation matrix is calculated by the inversion lemma, as shown in formula (3.30).

$$\mathrm{R}^{-1}(n) = \frac{1}{\lambda} \left[\mathrm{R}^{-1}(n-1) - \frac{\mathrm{R}^{-1}(n-1)\mathrm{u}^*(n)\mathrm{u}^T(n)\mathrm{R}^{-1}(n-1)}{\lambda + \mathrm{u}^T(n)\mathrm{R}^{-1}(n-1)\mathrm{u}^*(n)} \right] \tag{2.30}$$

Because the algorithm introduces the error term of MMA, it can solve the phase ambiguity of the signal. However, due to the inconsistency of nonlinear estimation in the algorithm, the formula (29) may have a divergence problem during the update process. In order to avoid this problem, the error term is normalized to obtain

$$\frac{e(n)}{\gamma} = d(n) - y(n) \tag{2.31}$$

Then, formula (2.29) can be rewritten as

$$\mathrm{W}_{out}(n) = \mathrm{W}_{out}(n-1) + [d(n) - y(n)]\mathrm{R}^{-1}(n)\mathrm{u}^*(n) \tag{2.32}$$

The error e(n) is written as $\gamma[d(n) - y(n)]$ and reflects the estimated quality of the transmitted signal. Although formula (2.32) is just a different way of writing formula (2.29), this form is more convenient. It includes all nonlinear terms in d(n), thus avoiding the bias caused by the inconsistency of nonlinear estimation. Among them, d(n) is:

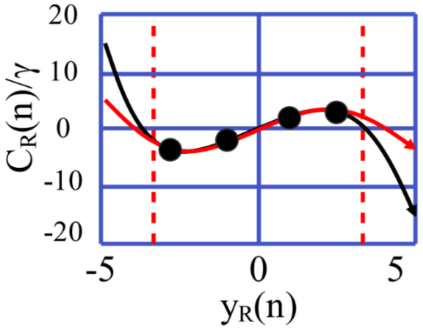
$$d(n)=d_R(n)+jd_I(n)=t_R(n)y_R(n)+jt_I(n)y_I(n) \tag{2.33}$$

Among them,

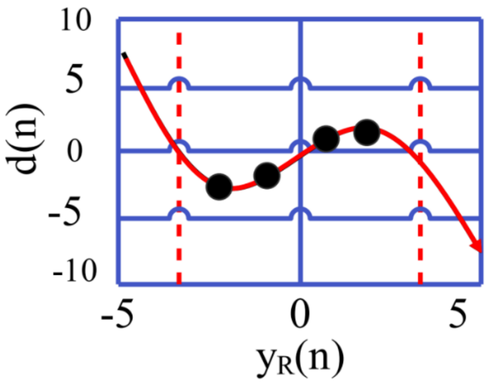
$$t_R(n)=\frac{3E\left\{s_R^2(n)\right\}-y_R^2(n)}{\gamma} \tag{2.34}$$

$$t_I(n)=\frac{3E\left\{s_I^2(n)\right\}-y_I^2(n)}{\gamma} \tag{2.35}$$

Because of $3E\left\{s_R^2(n)\right\}=3E\left\{s_I^2(n)\right\}>R_{MMA}$, it can be seen from formula (2.34) and formula (2.35) that when $y_R^2(n)<3E\left\{s_R^2(n)\right\}$ and $y_I^2(n)<3E\left\{s_I^2(n)\right\}$ are satisfied at the same time, $t_R(n)$ and $t_I(n)$ are positive. Therefore, $d_R(n)$ and $d_I(n)$ have the same sign as $y_R(n)$ and $y_I(n)$, respectively. Figure 2(a) and Figure 2(b) show the relationship of the error functions $e(n)/\gamma=d(n)-y(n)$ and d(n) with respect to the 16QAM estimated signal y(n), respectively. The values of these signals at the coordinates of the real part of the constellation symbols are denoted by ".". The coordinates of the real part of all 16QAM symbols are contained in the interval: $-\sqrt{3E\left\{s_R^2(n)\right\}}<y_R(n)<\sqrt{3E\left\{s_R^2(n)\right\}}$. In this interval, the change caused by $y_R(n)$ will cause only a small change in $e_R(n)$ and $d_R(n)$, and $y_R(n)$ and $d_R(n)$ have the same sign. If we set $d_R(n)=0$ outside the interval (dashed line in Fig. 2(b)), the normalized error $e(n)/\gamma=-y_R(n)$ grows linearly with (dashed line in Fig. 2(a)), thus avoiding divergence.



(a) Change curves of normalized errors $e(n)/\gamma$



(b) $d_R(n)$ with respect to $y_R(n)$

Figure 2: Change curves of normalized errors $e(n)/\gamma$ and $d_R(n)$ with respect to $y_R(n)$.

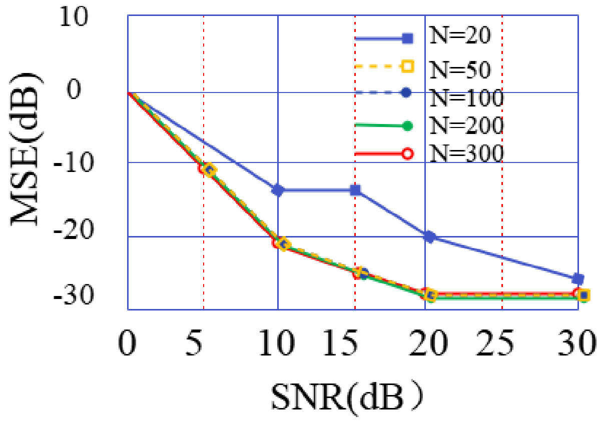
After the above analysis, in order to avoid the divergence problem in the iterative process of network output weights, a dual-mode operation scheme is used. The threshold for switching between the two modes is defined as: f $T=3E\left\{|S(n)|^2\right\}$. When $|y(n)|^2<3E\left\{|s(n)|^2\right\}$, the weight calculation is updated according to formula (32). When $|y(n)|^2>3E\left\{|s(n)|^2\right\}$ switches to the second mode, the expected value d(n) is ignored, that is, d(n)=0. Although the operation process of the second mode will affect the equalization effect of the signal, it can make the Euclidean norm of the output weight of the ESN decrease with the iteration of the algorithm, thus avoiding the divergence of the algorithm.

2.2 Simulation Experiment

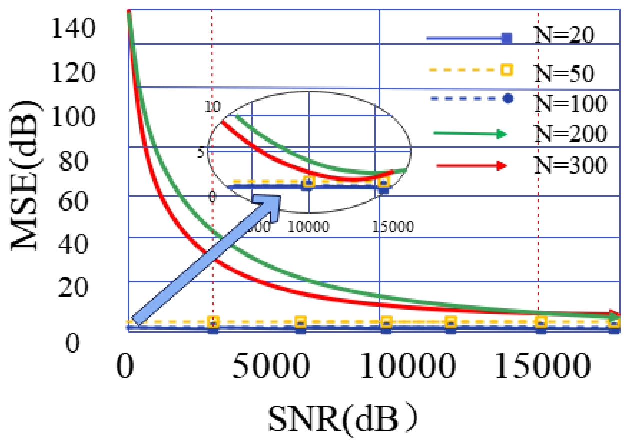
In this experiment, the memory depth is set to M=4. The transmitted signal s(n) is randomly generated and satisfies the independent and identical distribution, and the zero-mean Gaussian white noise is added, and the signal-to-noise ratio of the received signal is SNR=30dB. In both algorithms, the forgetting factor and pass cross-validation are set to 0.99 and 0.01, respectively. Taking the mean square error MSE as the evaluation standard of the algorithm, the calculation formula is:

$$MSE=\frac{1}{L}\sum_{n=1}^{L}(y(n)-s(n))^2$$

The experimental platform is CPU: Intel(R) Corei7-77003.6GHz; Windows1064bit; MATLABR2014b. In this group of experiments, the scale N of the ESN teaching simulation system, the activation function $f(\cdot)$ and the readout function $f_{out}(\cdot)$ are used as parameter variables to verify the effect of different parameter settings of the ESN on the balanced performance of the two algorithms. In order to ensure the stability of the network and the necessary sparsity, avoid the state explosion of the teaching simulation system, and make the network have "echo" characteristics, the spectral radius of the neuron connection weight W_{res} of the ESN teaching simulation system is set to $\rho\left(W_{res}\right)=0.9$, and the sparsity is SD=0.2 For the normal-mode QPSK signal and the multi-mode 16QAM signal, two algorithms, ESN-RLS-CMA and ESN-RLS-MMA are used for equalization respectively.



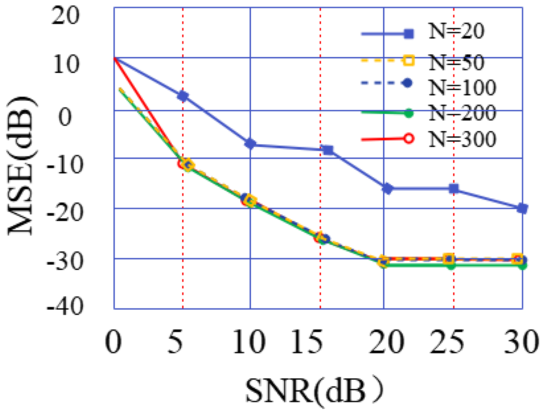
(a)



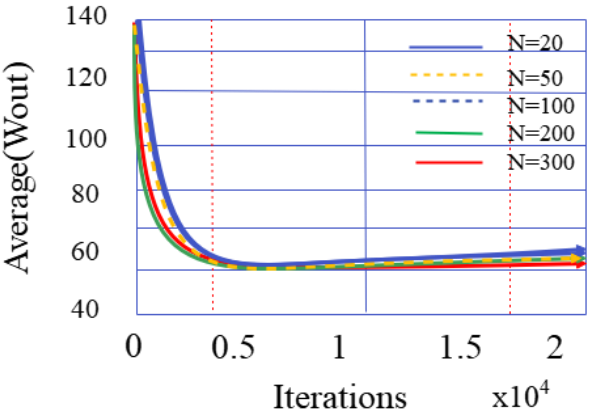
(b)

Figure 3: Influence of teaching simulation system scale N on the performance of ESN-RLS-CMA.

Fig. 3 is the influence curve of ESN-RLS-CMA by the scale N of the network teaching simulation system under the QPSK modulation signal. Figure 3(a) shows that when the number of neurons in the teaching simulation system is too small, such as N=20, its nonlinear mapping ability is weak. However, the mean square error MSE value after equalization is large, and the performance of the equalizer is poor. When the scale N of the teaching simulation system exceeds 50, the balanced performance of the algorithm is almost the same. Figure 3(b) shows the average cost value of the algorithm. It can be seen from the figure that the size of the teaching simulation system N also affects the convergence speed of the algorithm. When N is 200 or 300, the convergence speed of the algorithm is significantly reduced. In addition, the experimental results show that as the scale N of the teaching simulation system increases exponentially, the running time of the algorithm increases approximately exponentially by 2, so choosing the appropriate scale N of the teaching simulation system has an important impact on ESN-RLS-CMA.



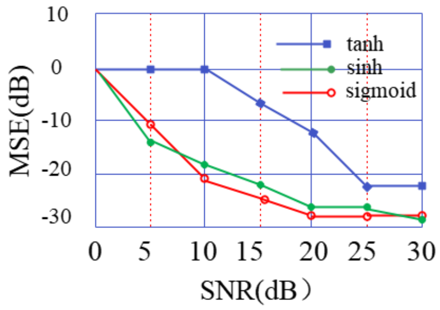
(a)



(b)

Figure 4: Influence of teaching simulation system scale N on the performance of ESN-RLS-MMA.

Figure 4 is the influence curve of ESN-RLS-MMA by the scale N of the teaching simulation system under the 16QAM modulation signal. It can be seen from Figure 4(a) that when the scale N of the teaching simulation system is 20, the MSE value after equalization is about 10dB larger than the MSE value when N is larger. When N exceeds 50, choosing different N has little effect on the performance of the equalizer, which is similar to ESN-RLS-CMA. Figure 4(b) shows that the convergence speed of the algorithm is not greatly affected by the scale N of the teaching simulation system. It is different from ESN-RLS-CMA. However, considering the running time of the algorithm, the scale N of the teaching simulation system should not be too large



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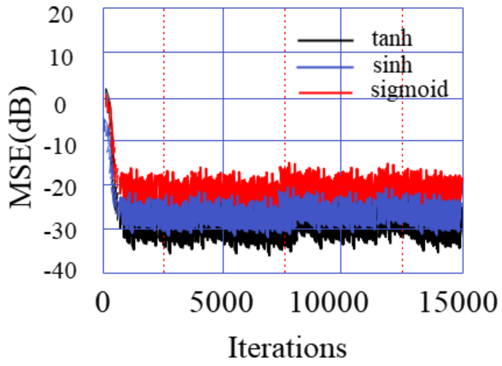
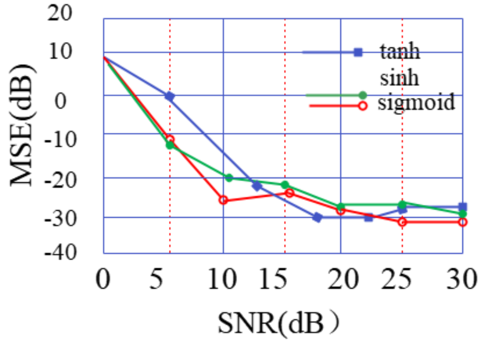
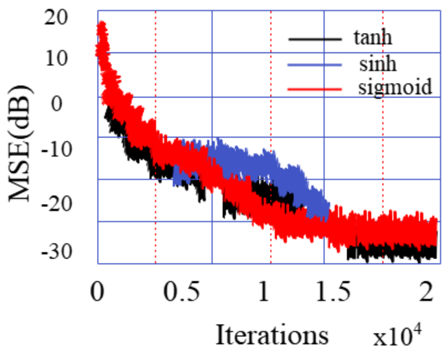


(b)

Figure 5: Effect of activation function f(•) on the performance of ESN-RLS-CMA.



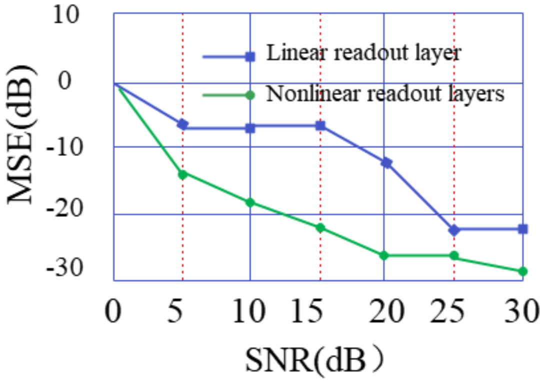
(a)



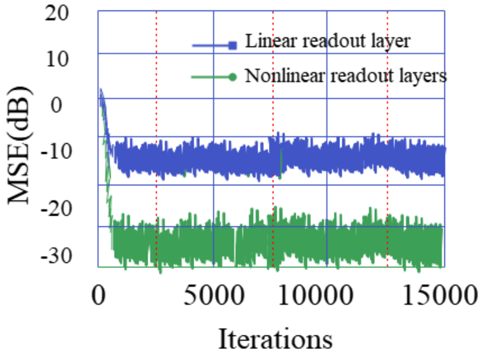
(b)

Figure 6: Effect of activation function f(•) on the performance of ESN-RLS-MMA.

Figure 5 and Figure 6 are the performance comparison curves of ESN-RLS-CMA and ESN-RLS-MMA when different activation function $f(\cdot)$ are selected, respectively. Comparing Figure 5(a) and Figure 6(a), it can be seen that the effect of different activation functions on ESN-RLS-CMA is more obvious than that of ESN-RLS-MMA. For ESN-RLS-CMA, the MSE value when the $sigmoid(\cdot)$ activation function is selected is significantly larger than the MSE value when the activation functions are f $tanh(\cdot)$ and $sinh(\cdot)$, and the maximum difference reaches 14dB. In ESN-RLS-MMA, the effect of different activation functions on the MSE value is relatively small. Comparing Figure 5(b) and Figure 6(b), it can be seen that for the ESN-RLS-CMA algorithm, three different activation functions are selected, and the algorithm converges in about 1000 iterations. For the ESN-RLS-MMA algorithm, due to the dual-mode operation, the algorithm has two convergence processes. When the activation function is selected as $tanh(\cdot)$, the algorithm converges for the first time in about 5000 iterations. However, when the other two numbers are selected, the second convergence of the algorithm requires about 12,000 iterations, and when the other two activation functions are selected, the second convergence of the algorithm requires about 15,000 iterations.

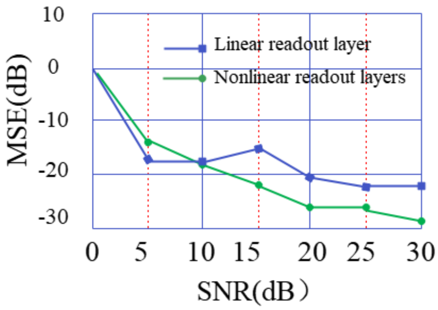


(a)

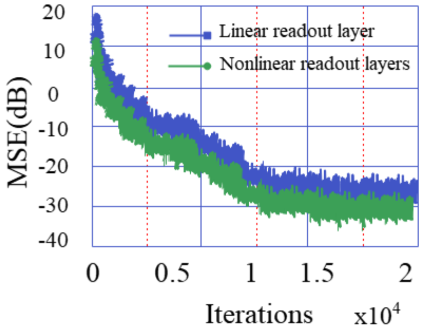


(b)

Figure 7: The effect of network readout layer function f_{out} on the performance of ESN-RLS-CMA.



(a)



(b)

Figure 8: The effect of network readout layer function f_{out} (•) on the performance of ESN-RLS.

Figures 7 and 8 respectively show the performance curves of the two algorithms when N is 100, the activation function $f(\cdot)$ is $tanh(\cdot)$ and ESN selects different output layer readout functions $f_{out}(\cdot)$. In the experiment, the linear function and the nonlinear function are respectively used as the readout function of ESN to analyze the convergence performance of the algorithm. The linear readout function is $f_{out}(\cdot)=1$, and the nonlinear readout function is $f_{out}(y)=g(y)+jg(y), g(y)=y+\beta sin(\pi y), \beta=0.3$.

Figure 7 shows the performance curve of ESN-RLS-CMA under QPSK signal. It can be seen from Figure 7(a) that with the increase of SNR, the nonlinear readout layer exhibits better equalization effect than the linear readout layer, and the MSE difference between the two can reach $13dB$ at most. Figure 8 shows the equalization performance curves of ESN-RLS-MMA when different readout layer functions are selected under 16QAM signal. It can also be seen from Figure 8(a) that with the increase of SNR, the MSE value of the nonlinear readout layer is lower than that of the linear readout layer. For example, when $SNR=30dB$, the MSE value of the nonlinear readout layer is about $-30dB$, and the MSE value of the linear readout layer is about $-25dB$, and the difference between the two is about $5dB$. Comparing Figure 7(b) and Figure 8(b), it can be seen that the convergence performance of ESN-RLS-CMA is roughly the same when different readout layer functions are selected, and they all converge in about 1000 iterations. However, ESN-RLS-MMA has two convergence processes due to the addition of a dual-mode operation scheme. Whether the linear readout layer or the nonlinear readout layer is selected, the algorithm converges for the first time after about 5000 iterations, and the second convergence after about 15000 iterations.

3 ENGLISH INTERACTIVE TEACHING SYSTEM BASED ON COMPUTER NETWORK

Interactive activity is the smallest unit of activity theory to study people's life practice, and tools play an important role in it. Moreover, the activity theory emphasizes that the learning subject (the learner) must act on the object (the learner's goal) through the tool, and the tool plays a mediating role in it. In live teaching, teachers and learners are not in the same learning space. Interactive live broadcast technology, live broadcast platform, computer and mobile learning terminal are important tools to connect the subject and object, which can better explain the relationship between different elements such as the environment, subject, and intermediary in the live broadcast teaching situation. The English interactive teaching system based on computer network is shown in Figure 9.

This paper evaluates the English interactive teaching system based on computer network proposed in this paper, and analyzes it in combination with the actual situation. Starting from the actual situation, this paper conducts research through a variety of practical teaching, the promotion of the system to the English teaching system is counted, and the results shown in Table 1 are obtained. Through the above experimental research, it can be seen that the English interactive teaching system based on the computer network proposed in this paper can effectively improve the interactive effect of English teaching.

4 CONCLUSION

Teaching interaction is a process in which learners recognize new things, acquire new skills, or explore phenomena that did not exist in the past under specific backgrounds and circumstances. Teaching interaction cannot be completed independently, it includes the interaction between teachers and students, and between students.

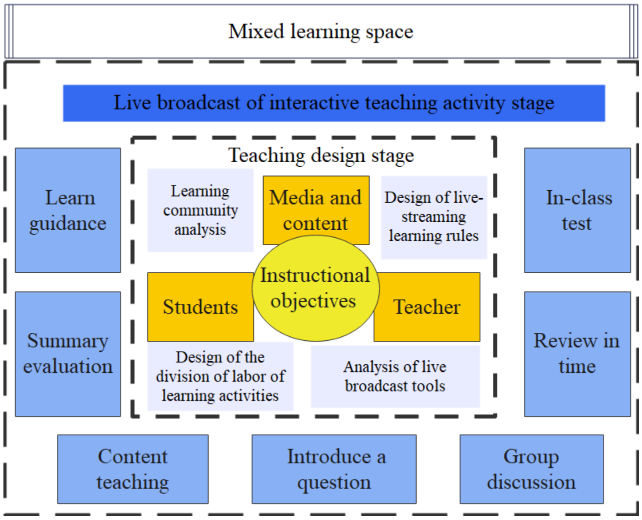


Figure 9: English interactive teaching system based on computer network.

Number	*Interactive effect*	*Number*	*Interactive effect*	*Number*	*Interactive effect*
1	*84.85*	*18*	*81.13*	*35*	*79.93*
2	*85.27*	*19*	*85.93*	*36*	*81.66*
3	*83.70*	*20*	*83.18*	*37*	*84.04*
4	*81.51*	*21*	*82.54*	*38*	*84.61*
5	*85.09*	*22*	*83.72*	*39*	*83.38*
6	*82.44*	*23*	*83.29*	*40*	*85.29*
7	*84.16*	*24*	*84.62*	*41*	*79.35*
8	*84.57*	*25*	*82.58*	*42*	*82.82*
9	*81.43*	*26*	*79.38*	*43*	*81.06*
10	*79.22*	*27*	*82.29*	*44*	*83.82*
11	*79.11*	*28*	*80.19*	*45*	*85.20*
12	*84.62*	*29*	*82.13*	*46*	*82.26*
13	*84.23*	*30*	*82.69*	*47*	*79.79*
14	*81.98*	*31*	*79.19*	*48*	*83.80*
15	*81.31*	*32*	*79.95*	*49*	*85.70*
16	*79.55*	*33*	*80.63*	*50*	*81.70*
17	*80.58*	*34*	*83.44*	*51*	*82.45*

Table 1: English interactive teaching system based on computer network.

Teacher student interaction and student student interaction are essential teaching methods. In addition, effective teaching interaction can make the classroom active and interesting, stimulate students' interest in learning, attract students' attention, and improve the efficiency of English classroom. This paper constructs an interactive English teaching model based on information technology and computer network technology, and studies the teaching practice effect after the model is constructed. The experimental research shows that the computer network technology for information fusion and clustering proposed in this paper can effectively improve the interactive effect of English teaching.

Conflict of interest

The author declare no competing interests.

Data Availability Statement

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

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