

Retraction

Retracted: Modeling and Simulation of English Speech Rationality Optimization Recognition Based on Improved Particle Filter Algorithm

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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.

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

- [1] H. Dong, "Modeling and Simulation of English Speech Rationality Optimization Recognition Based on Improved Particle Filter Algorithm," *Complexity*, vol. 2020, Article ID 6053129, 10 pages, 2020.

Research Article

Modeling and Simulation of English Speech Rationality Optimization Recognition Based on Improved Particle Filter Algorithm

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As one of the most important communication tools for human beings, English pronunciation not only conveys literal information but also conveys emotion through the change of tone. Based on the standard particle filtering algorithm, an improved auxiliary traceless particle filtering algorithm is proposed. In importance sampling, based on the latest observation information, the unscented Kalman filter method is used to calculate each particle estimate to improve the accuracy of particle nonlinear transformation estimation; during the resampling process, auxiliary factors are introduced to modify the particle weights to enrich the diversity of particles and weaken particle degradation. The improved particle filter algorithm was used for online parameter identification and compared with the standard particle filter algorithm, extended Kalman particle filter algorithm, and traceless particle filter algorithm for parameter identification accuracy and calculation efficiency. The topic model is used to extract the semantic space vector representation of English phonetic text and to sequentially predict the emotional information of different scales at the chapter level, paragraph level, and sentence level. The system has reasonable recognition ability for general speech, and the improved particle filter algorithm evaluation method is further used to optimize the defect of the English speech rationality and high recognition error rate. Related experiments have verified the effectiveness of the method.

1. Introduction

English speech rationality recognition is the product of the combination of emotion computing and speech synthesis. With the help of the concept of emotion computing, the relationship between emotion and speech is analyzed from the speech signal carrying the known emotional state, and these emotional features are applied to the speech synthesis process. In order to obtain natural and friendly synthesized speech with rich tone changes, which can simulate human emotions, current speech synthesis technology usually refers to text-to-speech conversion technology, which mainly solves how to convert text information into audible sound information. English speech interaction is a natural and convenient way for humans to communicate with machines in the future. Research on speech recognition is enough to promote this technology to serve humans faster and better.

Whether it is from the perspective of technology accumulation or data collection, the current period is a favorable period for studying speech recognition technology.

Particle filter algorithm [1, 2] is an online nonlinear identification algorithm based on Bayesian estimation and Monte Carlo method. Its essence is to approximate the state probability density function by finding a set of random samples propagating in the state space. A discrete sample is used to simulate a continuous function, and the sample mean is used to replace the integral operation, thereby obtaining the process of minimum variance distribution of the state. The particle filtering algorithm theoretically has higher recognition accuracy than the extended Kalman filter algorithm. The authors of [3, 4] improved the traditional particle filter algorithm and used the latest observation information in the importance sampling process to more accurately approximate the posterior probability density

function. The authors of [5, 6] proposed a resampling algorithm to solve the problem of particle degradation. The authors of [7–9] use particle filtering algorithm to solve the damage identification problem of structural systems. Research shows that, compared with EKF algorithm, particle filtering has higher structural model parameter recognition accuracy under non-Gaussian noise conditions. The authors of [10–12] use a hybrid Gaussian particle filter to predict and analyze the posterior distribution parameters and monitor values of the monitoring information state variables in one step forward. At present, the research and application of particle filters in civil engineering are still very limited. How to further improve the sampling accuracy of particle filter algorithms and weaken particles is still the key issue to improve the accuracy of the algorithm. The existing methods for synthesizing emotional speech mainly include three categories: waveform stitching, speech conversion, and statistical parameter synthesis. The waveform stitching method collects voices of different emotion types by recording a large-scale emotional corpus and extracts corresponding speech fragments from the corresponding emotional corpus during synthesis and obtains voices that retain the original recorded tone through stitching [13–15]. The voice conversion method analyzes the change of acoustic parameters of voices of different emotion types relative to neutral voices and adjusts and converts presynthesized neutral voices to obtain new emotional voices [16, 17]. Statistical parameter synthesis is based on statistical models such as Hidden Markov Models. It performs parametric characterization and acoustic modeling of speech with different emotions. Based on this, it performs acoustic prediction of emotional speech and synthesizes speech with different emotions [18–20]. At present, the three methods have their own advantages and disadvantages. The emotional speech that is properly combined by the waveform stitching method is better than other methods. However, the types of emotions that can be synthesized are limited by the existing emotion types of the emotional corpus. The cost of large-scale database building is high; English speech rationality optimization conversion method relies on the study of emotional acoustic feature analysis [21–23]. Due to the diversity and complexity of emotional performance, only some specific emotional states and directional cues were associated with changes in acoustic parameters: Statistical parameter synthesis methods can automatically build a new synthesis system in a short period of time, basically without human intervention, and require less data compared to waveform stitching methods and synthetic emotion types. It is more flexible than the previous two methods, but the spectrum and prosody model generated by HMM is too smooth, which makes the details of the spectrum and prosody model lost, affecting the naturalness of the English speech sound optimization and recognition. With the tremendous achievements of neural networks in many fields, many scholars have begun to study their applications in the field of speech recognition. A variety of models such as deep neural networks, convolutional neural networks, and recurrent neural networks have been introduced and achieved good results [24–26]. The system based on the state output of the deep neural network has a certain decrease in error rate compared

to the convolutional neural network, which proves the modeling ability of the neural network method in the field of English speech rationality optimization recognition [27, 28]. However, the method for optimizing the rationality of English speech based on deep learning requires a large amount of training data to ensure its accuracy. Compared with the traditional method, it also requires a larger amount of calculation, which also limits its application in practice to a certain extent.

Under the guidance of the English speech rationality optimization recognition process, a network structure is built. Using the annotation data of the speech sentiment database and the text features obtained based on semantic analysis, a deep learning model is trained to realize the prediction of the optimal recognition of the speech sound from reading text to English speech. The pronunciation description is used as the final result output of the prediction model to guide the generation of subsequent acoustic parameters. The model comprehensively considers the influence of the context environment of different scale units at the chapter level, paragraph level, and sentence level, as well as the interaction between the various links in the process of optimizing the recognition of English sound rationality, forming a multilayer-nested composite network to support structural construction. First, an improved auxiliary traceless particle filtering algorithm is established based on the standard particle filtering algorithm, and the algorithm implementation steps are given. Then, the online parameter identification for the single-degree-of-freedom model is carried out and compared with the identification results of the traditional particle filter algorithm to verify the accuracy and calculation efficiency of the improved algorithm. Finally, the pseudostatic test of the seismic isolation support verifies the effectiveness of the improved auxiliary traceless particle filter algorithm for online identification of model parameters. The rest of this paper is organized as follows. Section 2 discusses optimal recognition modeling of English speech rationality, and optimized recognition model of English sound rationality based on improved particle filter algorithm is designed in Section 3. Experimental verification is discussed in Section 4. Section 5 concludes the paper with summary and future research directions.

2. Optimal Recognition Modeling of English Speech Rationality

At present, English speech rationality optimization recognition technology is facing huge development opportunities. First, with the development of devices with high computing power, more complex algorithms and models become possible; second, with the help of massive data on the Internet, it becomes easier to have corpus resources in real scenes, making the trained models more reasonable; finally, the rise and popularity of applications such as smart homes, car systems, and mobile devices make voice, a convenient human-computer interaction, more important. The optimal recognition of English speech rationality can be divided into four main parts, namely, data preprocessing and feature extraction, language model, acoustic model, and decoder, as shown in Figure 1.

The data preprocessing part is performed before the identification and decoding, including the signal preemphasis, framing, windowing, and other operations [29]. Research has found that the energy of speech is mainly in the low frequency range, which may lead to an excessive signal-to-noise ratio in the high frequency range. Preemphasis can enhance the high frequency band of speech to make its characteristics more prominent. English speech is a non-stationary time-varying signal, but it has a short-term stationary characteristic when the duration is short, so its signal processing needs to be performed after framing. By framing the signal, each frame can be regarded as a smooth signal. Generally speaking, the duration of each frame is between 10 and 30 ms and there will be overlap between frames. After framing, it will cause discontinuity at the beginning and end of each frame. Windowing is to highlight the signal in the middle and make it continuous. The window function usually chooses the Hamming window.

Feature extraction is mainly to extract some information that can reflect the commonality from the signal. When different speakers speak the same paragraph of text, the pronunciation will be different due to the difference in vocal organs and speaking habits. Feature extraction is to remove these characteristics. The feature used by the system in this paper is the MFCC feature, which is one of the commonly used features in the field of speech recognition.

The purpose of English speech rationality optimization recognition is to convert speech into text. After the system receives a piece of audio, it can find the most reasonable sequence of words to represent the information contained in this piece of audio. We define the speech signal as T and the text sequence as M ; then the optimization and recognition of English sound rationality need to be solved:

$$M = \arg \max P(M | T). \quad (1)$$

That is, on the premise of knowing the voice T , find the most likely text sequence M . According to the Bayesian formula, we can change the above formula to

$$M = \arg \max \frac{P(T | M)P(M)}{P(T)}, \quad (2)$$

For a particular piece of audio T , P is fixed and therefore does not need to be considered in the optimization process. The above formula is the core formula of speech recognition, which can be seen as a combination of two parts, the language model $P(M)$ and the acoustic model $P(T | M)$; the language model represents a certain sequence of text M in language habits rationality.

The main function of the decoder is to use the trained language model and acoustic model to build a decoding network, search in the network, and finally find the optimal path that can explain the input speech and give the recognition result. The decoder can search through a given input feature sequence and finally find and use the decoding algorithm to best interpret the input audio text sequence for the search composed of the language model and the acoustic model.

Feature selection is a link that has a significant impact on the optimization of the recognition efficiency of English

speech. Deciding which acoustic features to use will largely affect the recognition rate of the system. The acoustic features commonly used in the optimization and recognition of English speech rationality include perceptual linear prediction, linear prediction coefficients, and Mel-frequency cepstral coefficients, and cepstral features are commonly used Mel-frequency cepstral coefficients. The Mel-frequency is the cepstral parameter extracted from the frequency domain of the scale. It has a high degree of similarity to the human auditory characteristics. Mel-frequency cepstral coefficient can perfectly combine the frequency selection characteristics of ear-to-sound and speech signal processing technology. It has strong robustness and noise resistance. It is one of the most effective features in the field of English speech sound optimization recognition.

The extraction process of English speech rationality optimization recognition features is shown in Figure 2.

Before extracting the English speech rationality optimization recognition feature for the audio signal, we need to perform relevant preprocessing operations on the data. The power of the voice signal will be very small when the frequency is large. The main energy is distributed in the low frequency band. This may cause the signal-to-noise ratio of the high frequency band to be too large. Preemphasis can enhance the high-frequency signal of the voice. Speech is a nonstationary signal, but it is stationary for a short period of time. The framing and windowing operations are to take advantage of this short-term stationarity to divide the long-term nonstationary signal into multiple frames of shorter stationary signals. Generally speaking, the length of each frame of speech is between 10 and 30 ms, and there is overlap between the frames, which can ensure the continuity of the signal. The window function used in this article is the Hamming window, which can be expressed as

$$M(n) = \begin{cases} 0.5 - 0.48 \cos \frac{2\pi n}{M-1}, & 0 \leq n \leq M \\ 0, & \text{OTHER.} \end{cases} \quad (3)$$

After preprocessing the English speech signal, we use fast Fourier transform to transform the obtained short-term signal $p(1)$ into time frequency and calculate the short-term energy spectrum $h(1)$. Then we use the filter $c(1)$ to process the short-term energy spectrum, followed by using the filter to process the short-term energy spectrum; the formula can be expressed as

$$M(j) = \begin{cases} \frac{j - p(1)}{c(1) - p(1)}, \\ \frac{h(1) - j}{j(1) - c(1)}. \end{cases} \quad (4)$$

Then, we make logarithmic changes to the output of the filter bank and finally through the discrete cosine transform to obtain the English speech rationality optimization recognition feature coefficients.

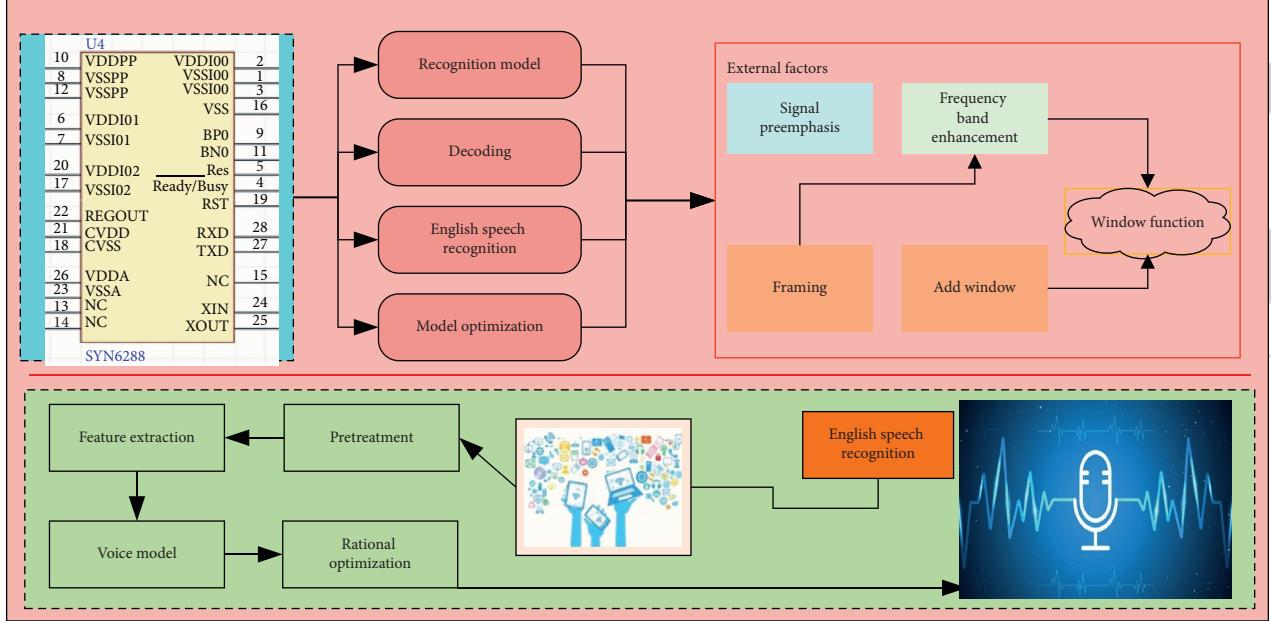


FIGURE 1: English speech rationality optimization recognition framework.

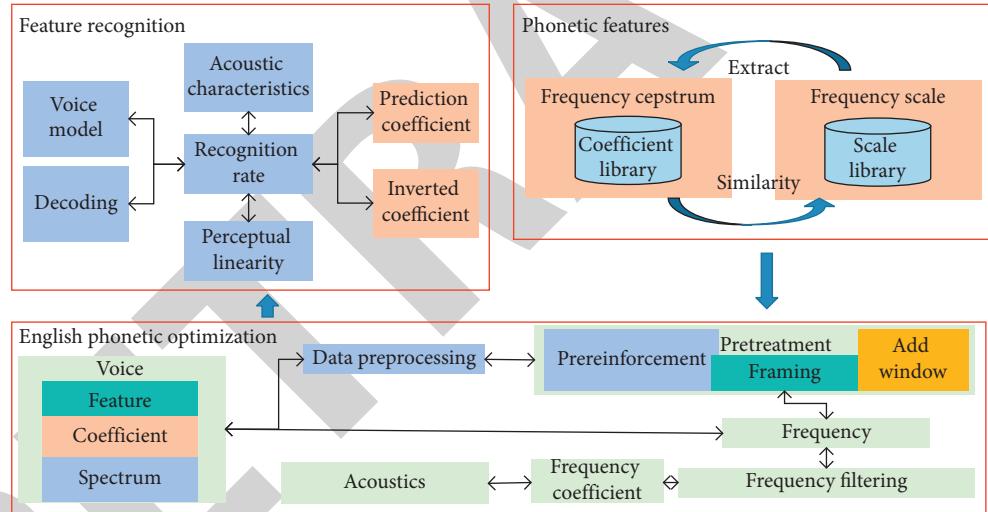


FIGURE 2: English speech rationality optimization recognition feature extraction process.

3. Optimized Recognition Model of English Sound Rationality Based on Improved Particle Filter Algorithm

3.1. Reasonable Optimization of Identification Parameters. The improved particle filter algorithm inherits the principle of the particle filter algorithm and is a complete nonlinear estimator that can identify arbitrary nonlinear model parameters. The improved particle filter algorithm model is a representative strong nonlinear model used to simulate the restoring force characteristics of structures and members. In this paper, the single-degree-of-freedom improved particle filter algorithm model is taken as the object, and a specific implementation method of applying the algorithm to online identification of nonlinear model

parameters is given to verify the algorithm recognition accuracy.

Combined with structural motion equation, particle filter algorithm model was improved.

Set the model parameter of the improved particle filter algorithm to the actual value of $k_0 = 40 \text{ kN/m}$, $n = 1.1 \text{ t}$; load the model with displacement control, input displacement excitation, and select the ground motion displacement record measured by the seismic station; the peak displacement is adjusted to 10 cm, as shown in Figure 3, vertical. The coordinates are displacement. Using the fourth-order numerical integration method to calculate the resilience of the improved particle filter algorithm model system, the integration step length is 0.01 s, and the integration number of steps is 4000 steps.

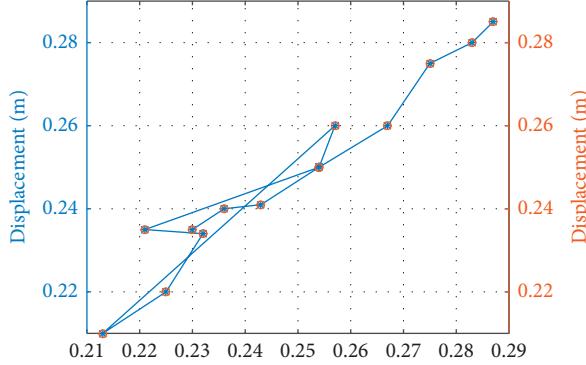


FIGURE 3: Displacement loading time history curve.

z is the process noise; k is the actual loading speed; n is the number of times; the system state equation is

$$y = f(y, y') = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} - \begin{bmatrix} z \\ k \\ \dots \\ n \end{bmatrix}. \quad (5)$$

3.2. Stepped Resampling Improvements. In order to solve the problems of sample degradation and reduced estimation accuracy caused by resampling, this paper proposes a particle selection scheme based on the bias-corrected exponential weighted average algorithm and then effectively uses the remaining large-weight particles to complete the replication and new number addition ensure the final particles meets the initial total.

Aiming at the problem that standard resampling directly removes small particles and reduces the filtering performance, the following particle screening strategy is designed: (1) Calculate the weight of particles and arrange them in ascending order. (2) Use the EWA optimization algorithm based on deviation correction to calculate the sorted particle set. The average distribution curve of the expression is:

$$\gamma_i = \frac{\varepsilon y_{i-1} + (1-\varepsilon) \omega_t^i}{1 - \varepsilon^i}. \quad (6)$$

In the previous equation, γ_i , y_{i-1} is the average weight of the first i , $i-1$ particles, ε is the overshoot parameter, ω_t^i is the weight of the i -th particle, and $1 - \varepsilon^i$ is the deviation correction term. (3) Calculate the average value of the γ_i curve and judge the particle weight γ with the size of ω_t^i ; if $\omega_t^i \geq \gamma$, the particle is left and then is discarded. The exponentially weighted average optimization algorithm takes into account the fact that large-weight particles are the decisive factor that affects the estimation accuracy, and the introduction of deviation correction items reduces the previous calculation errors, improves the accuracy of particle screening, and also ensures the effectiveness of replication and new particles.

The process of optimizing the recognition of English speech rationality is divided into two parts: the training stage and the formal stage. The training stage first selects 10

articles for independent labeling, and then several labelers compare the results and discuss the labeling rules. The three annotation results are summarized and integrated into the final annotation result of each document by the introduction method in the next section. The agreement rate of the three labeling results in different scales is shown in Table 1. It can be seen from the table that the labeling agreement rates of the three scales are similar, and the chapter-level agreement rate is slightly higher than the other two levels; the agreement rate between two people is better than that of the three people, but the common agreement rate is also close to 80%, reaching a usable level.

3.3. English Speech Rationality Optimization Keyword Recognition Model. Let the English speech rationality optimization keyword recognition system have the rejection function; a feasible method is to use the junk speech model to improve the decoding network. In the training phase, each phoneme model is trained with the corpus of the corresponding phoneme, and the junk speech model uses all corpus for training, so it can be considered that it represents the human voice model rather than a specific phoneme. All voices have a certain matching ability.

Real time is an important feature of human-machine voice interaction. Whether the system can recognize the voice in time will play a vital role in the promotion of user experience and applications. The main time-consuming of the keyword speech recognition system is the decoding efficiency of English speech, so how to improve the efficiency of the decoding algorithm is the key to improving the performance of the system. The Viterbi decoding algorithm needs to search all possible states of the entire decoding network every frame. The token-passing decoding algorithm we mentioned is a specific implementation of the Viterbi decoding algorithm, which has the characteristics of simple search process implementation, thereby reducing the decoding time and improving system performance. However, the token transfer algorithm also cannot avoid the shortcomings of the whole network search. All tokens of the decoding network in each frame need to be transferred between all possible states. When the number of system states increases, the decoding time will also be large, in addition to an increase in amplitude.

The token-passing decoding algorithm searches through the entire network to ensure that the best state path is found. After obtaining the voice characteristics of each frame, all tokens in the decoding network will jump, although this can guarantee that each path can be searched, but it also limits the performance of the algorithm. Performing a network-wide search will consume a lot of computing resources on some paths with very low probability. In fact, these paths have a long distance from the token value at the beginning due to their low matching with the speech to be recognized. Lower than other tokens, the probability of these paths gaining an advantage in subsequent competition is very low, so these tokens can be discarded earlier to prevent their passing down, thereby reducing the consumption of computing resources and improving algorithm performance.

TABLE 1: Statistics of the coincidence rate of the labeling results.

	A&B	A&C	B&C	A&B&C
Chapter level	0.8264	0.843	0.8525	0.7821
Paragraph level	0.8275	0.8392	0.8483	0.7798
Sentence level	0.8267	0.8378	0.8468	0.7788
All	0.8269	0.8389	0.848	0.7795

"A," "B," and "C" represent the three labeling personnel.

In the specific implementation, the maximum number of tokens should be set reasonably according to the complexity of the network. If the maximum number of tokens is set too large, the system performance will cause many paths to be discarded per frame. The improvement is very limited. However, the maximum number of tokens is set too small to include the best path, which leads to a reduction in the accuracy of system identification. Therefore, when setting the maximum number of tokens, the performance and accuracy should be taken into consideration.

4. Experimental Verification

In order to verify that the algorithm in this paper has good filtering performance, MATLAB simulation software is used to compare and analyze the number of particles with 50, 100, and 150 based on the univariate dynamic change filter model. Based on the improved particle filter algorithm, unified particle filter algorithm, scheduling particle filter algorithm, and particle filter algorithm, the English speech rationality optimization keyword recognition model's online parameter recognition results obtained by four algorithms are compared, as shown in Figure 4. It can be seen that the four algorithms for k_0 and n_2 parameters have the same recognition effect, basically converging to the true value, and the convergence speeds are roughly similar. Among them, the recognition value obtained by the improved particle filter algorithm is the best. The improved particle filter algorithm has higher nonlinear transformation accuracy in importance sampling, enriches the diversity of particles during the resampling process, and effectively weakens the degradation of particles. The performance of the algorithm determines the pros and cons of the recognition result of the calculation example, which is of universal significance. Therefore, when the actual value is of the keyword recognition model parameters for English sound rationality optimization in the calculation example changes, under the same conditions, the recognition results of the four algorithms will still have similar rules.

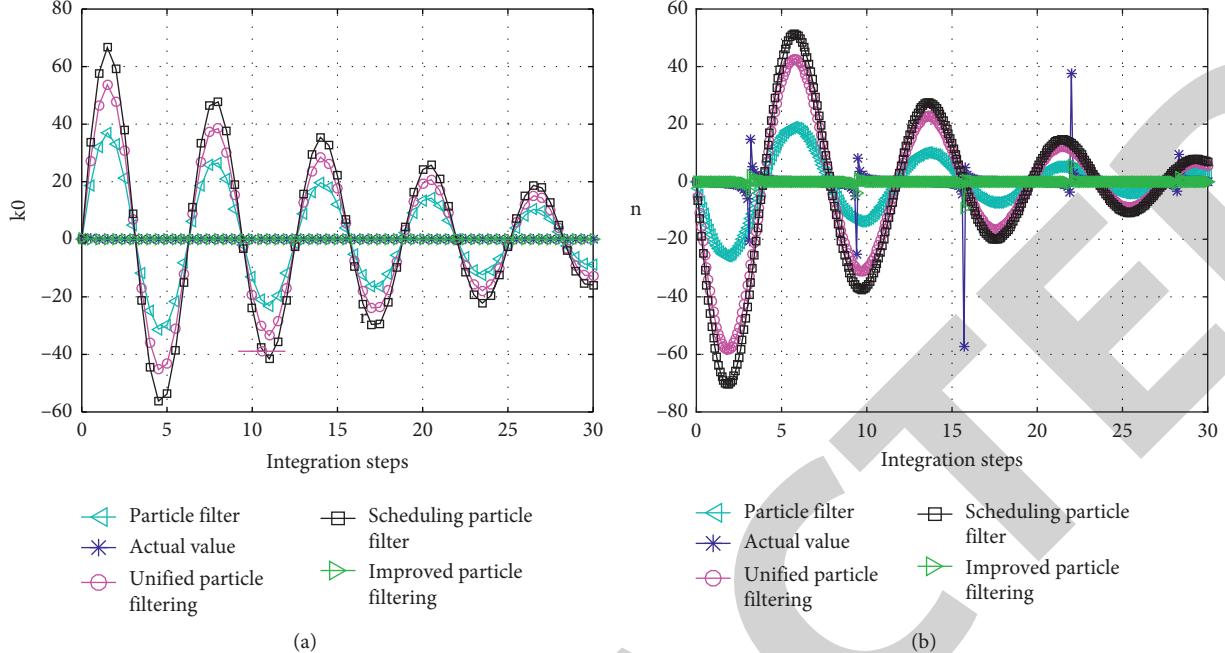
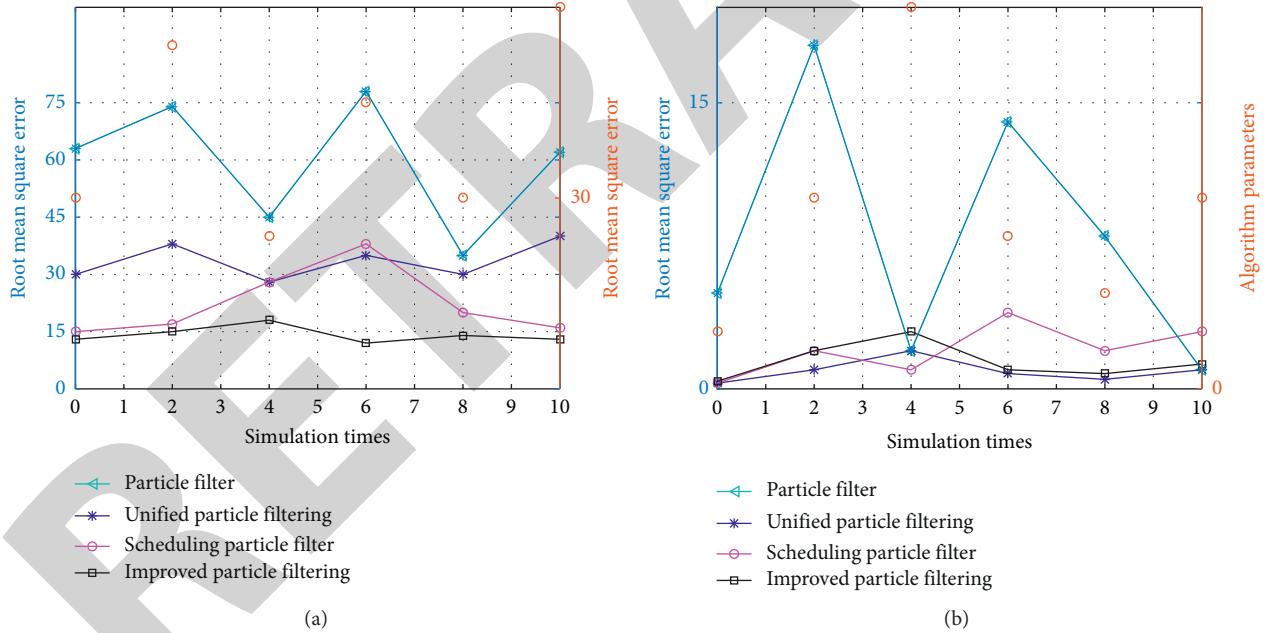
The particle filter algorithm and its improved scheduling particle filter algorithm and the unified particle filter algorithm and the improved particle filter algorithm are essentially random parameter identification algorithms. The four algorithms are all based on the Monte Carlo random sampling method. Therefore, even under the same condition of initial parameter values, the parameter identification values obtained by each algorithm in each simulation are different; that is, the parameter identification results are random. In order to test the randomness of the recognition results of the algorithm, four independent filtering

algorithms were used for 10 independent simulations. The statistical recognition results compared and analyzed the recognition accuracy and convergence of different algorithms, which was more convincing. In the 10 independent simulations in this example, the initial parameters of the system English sound rationality optimization recognition model and the initial parameters of the algorithm are the same. The randomness mainly comes from the randomness of the particles produced by the algorithm. The relationship between the root mean square error of the four algorithms' parameter identification values and the number of simulations is shown in Figure 5. The abscissa in the figure is the number of simulations.

It can be seen from Figure 5 that the overall error of the parameter identification of the improved particle filter algorithm is significantly lower than that of the particle filter algorithm, the scheduling particle filter algorithm, and the unified particle filter algorithm, and the error fluctuation range is significantly reduced. It can be seen that the improved particle filtering algorithm uses the latest observation information to modify the particles and at the same time increases the particle diversity by introducing auxiliary factors. Therefore, the improved particle filter algorithm is significantly higher than the recognition accuracy of the particle filter algorithm, scheduling particle filter algorithm, and unified particle filter algorithm.

As shown in Figure 6, the root mean square error mean and relative error mean of the online independent parameter identification value was calculated under independent simulations. It can be clearly seen that the mean value of the root mean square error and the relative error of the parameter identification value of the improved particle filtering algorithm proposed in this paper are smaller than those of the particle filtering algorithm as a whole. The root mean square error of the four sets of parameter identification values obtained by the improved particle filter algorithm is overall lower than those of the particle filter algorithm, scheduling particle filter algorithm, and unified particle filter algorithm. The error is reduced by 76%, 38%, and 23%, respectively, and, in the improved particle filter algorithm, the relative errors of the obtained four sets of parameter identification values as a whole are reduced by 22%, 16%, and 14% compared to the particle filter algorithm, scheduling particle filter algorithm, and unified particle filter algorithm. It can be seen that the average root mean square error and the average relative error of the four sets of parameter identification values in 10 simulations indicate that the accuracy of the improved particle filtering algorithm is higher than that of the other three algorithms. It should be noted that the algorithm needs to pay more time for calculation while achieving higher parameter recognition accuracy.

When we only use the improved English speech rationality of the particle filtering algorithm to optimize the keyword recognition modeling model for token-passing decoding, because there is no adjustable parameter, the equal error rate cannot be measured, and the false rejection rate of the system measured by the test set is only 1.24%, but the false alarm rate is as high as 76.05%, which shows that the system with only the improved particle filter algorithm

FIGURE 4: English speech rationality optimization keyword recognition value. (a) k_0 . (b) n .FIGURE 5: Root mean square error of model parameter identification value. (a) k_0 . (b) n .

model is very weak for nonkeyword speech recognition, and it is difficult to apply it in practice. We use the verification set to adjust the parameters and use the test set to test the results and finally measured the equal error rate of several different systems. The results are shown in Table 2.

In this paper, the improved particle filtering algorithm proposed in this paper optimizes the stability of English speech keyword optimization modeling, which indicates whether the optimal token on the decoding path can maintain a stable advantage in the competition during the

decoding process. If the decoding path is the correct keyword path, then it should be able to stay ahead of the competition by constantly accumulating advantages. If the decoding path is wrong, the optimal token on this path will not be compared to other paths, and there is a big difference.

As shown in Figure 7, when the voice to be recognized is a keyword, the optimal token on the decoding path of each frame can stably maintain an advantage in the competition, and this advantage will increase as the number of decoded frames increases.

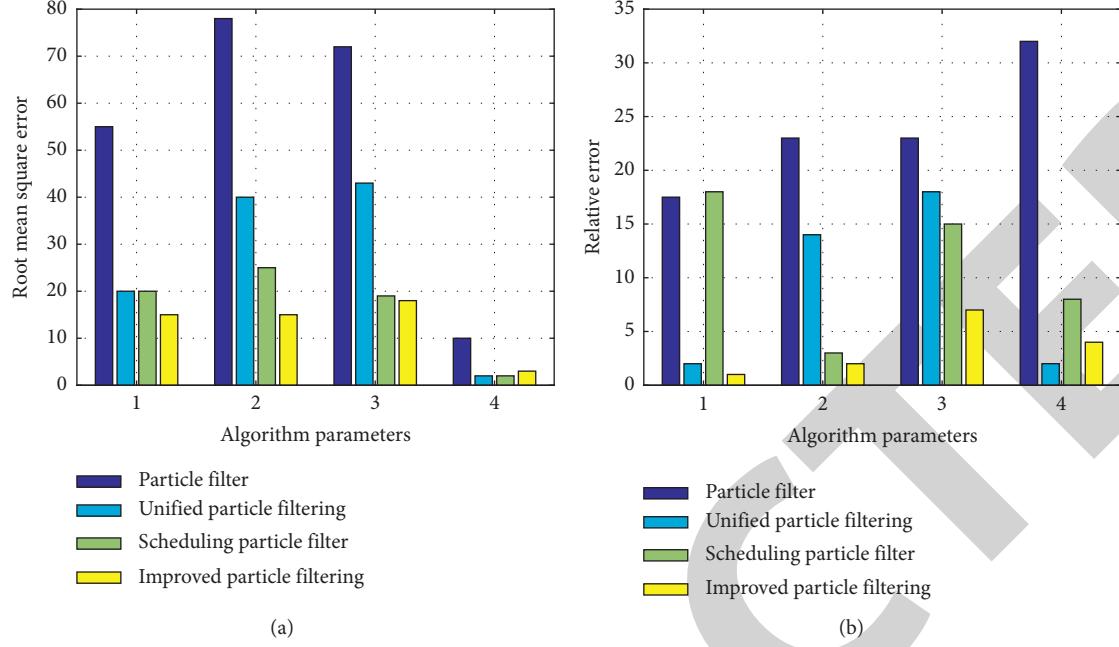


FIGURE 6: Root mean square error of parameter identification value and mean value of relative error. (a) Root mean square error. (b) Relative error.

TABLE 2: Different English pronunciation rationality optimization recognition error rate.

Method	Error rate (%)
Particle filtering algorithm [4]	16.84
Scheduling particle filter algorithm [12]	12.83
Unified particle filtering algorithm [15]	7.83
Improved particle filtering algorithm	5.73

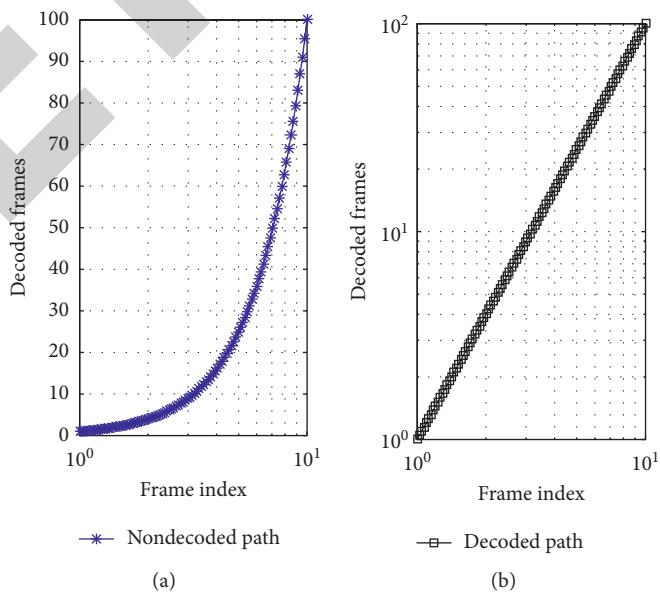


FIGURE 7: Stability data when the voice to be recognized is a keyword.

In this paper, the visibility modeling strategy of the deep neural network in the middle layer can effectively integrate prior knowledge into the network structure, thereby improving the performance of the network; optimization measures such as feature dimension balance adjustment and sample balance adjustment can solve the network learning process to a certain extent. The fusion problem between different types of features solve sample sparseness

5. Conclusion

In this paper, by introducing an improved particle filtering algorithm, the English speech rationality optimization recognition model enables the system to reject nonkeyword speech, which can be more widely used in actual scenarios. In order to improve the recognition accuracy and rejection ability of the speech keyword recognition system and make the application of the system more mature, on the basis of studying the principle of decoding algorithm, the data generated by the token transfer process in the preliminary experiment is analyzed, and finally two methods of consistency and stability were proposed and used to evaluate and correct the system identification results; and related experiments were set up to test the feasibility of the proposed method. The improved English speech rationality optimization recognition model with improved particle filter algorithm has high positioning accuracy and good stability, and its effectiveness is verified through experimental verification.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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