

Retraction

Retracted: Optimization Simulation of English Speech Recognition Accuracy Based on Improved Ant Colony 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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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

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

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

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Jing, "Optimization Simulation of English Speech Recognition Accuracy Based on Improved Ant Colony Algorithm," *Complexity*, vol. 2020, Article ID 8858399, 10 pages, 2020.

Research Article

Optimization Simulation of English Speech Recognition Accuracy Based on Improved Ant Colony Algorithm

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This paper is aimed at the problems of low accuracy, long recognition time, and low recognition efficiency in English speech recognition. In order to improve the accuracy and efficiency of English speech recognition, an improved ant colony algorithm is used to deal with the dynamic time planning problem. The core is to adopt an adaptive volatilization coefficient and dynamic pheromone update strategy for the basic ant colony algorithm. Using new state transition rules and optimal ant parameter selection and other improved methods, the best path can be found in a shorter time and the execution efficiency can be improved. Simulation experiments tested the recognition rates of traditional ant colony algorithm and improved ant colony algorithm. The results show that the global search ability and accuracy of improved ant colony algorithm are better than traditional algorithms, which can effectively improve the efficiency of English speech recognition system.

1. Introduction

Voice is a commonly used and important information when communicating between people. Voice recognition technology is a technology that allows machines to convert human voice signals into corresponding commands through recognition and understanding. Voice is a common and important information used in communication between people [1]. When people need to express some kind of information, they must use the voice signal that carries the information. The speech signal not only contains information about semantic content but also contains information about the speaker's personal identity. The basic basis of speech recognition is that each speaker has different characteristics due to his own unique vocal tract characteristics and pronunciation characteristics [2]. Speech recognition technology is a cross-discipline involving signal processing, pattern recognition, sound mechanism and hearing mechanism, artificial intelligence, and other fields. At present, speech recognition is gradually becoming the key technology of human-computer exchange in information technology. With the improvement of continuous speech recognition rate, speech recognition input has gradually become one of the important forms of computer input.

Ant colony algorithm (ACA) is a bionic optimization algorithm derived from the research of ants' foraging process in nature. It makes full use of the information exchange and cooperation between ants and finally finds a short path from ant nest to food source. Ant colony algorithm has distributed characteristics and strong robustness and is easy to be combined with other optimization algorithms [3]. In the early 1990s, Italian scholar Dorigo and others proposed ant colony algorithm, and the algorithm has been widely used in different combinatorial optimization problems, such as solving the assignment problem (QAP), vehicle routing problem (VRP), and job shop scheduling problem (JSP); a series of NP complete problems have been achieved. Ant colony algorithm has many excellent characteristics and is easy to combine with other methods. In the speech recognition system based on template matching, the time warping algorithm compares the reference template with the test template, maps it on a plane, and searches an optimal path from the starting point to the end point according to certain criteria [4]. This is a local optimization algorithm, each step of the search is based on the judgment of local optimization, and the ant colony algorithm can just solve the defect that the time planning path cannot reach the global optimization,

which also provides the feasibility for the application of ant colony algorithm in speech recognition.

This article first discusses the key technologies of speech signal preprocessing, endpoint detection, and feature parameter extraction in detail and introduces the basic principles of basic ant colony algorithm in detail. Then, for English speech recognition, dynamic time warping (DTW), an improved ant colony algorithm, is proposed for the problems of overreliance on the detection accuracy of voice endpoints, long recognition time, and low recognition efficiency. Its core is aimed at the basic ant colony algorithm, using adaptive volatilization coefficients, dynamic pheromone update strategies, new state transition rules, and optimal ant parameter selection, as well as other improved methods, so that the algorithm can find the best in a short time path to improve execution efficiency. The simulation experiment tested the recognition rate based on the traditional ant colony algorithm and the improved ant colony algorithm, respectively. The results show that the algorithm can find a better scheduling strategy in a shorter time and improve the global search ability and accuracy of the ant colony and can effectively improve the efficiency of the speech recognition system.

2. Related Theories and Technologies

2.1. Speech Recognition System. At present, there are many different system design and implementation methods for speech recognition systems. There are many types of classification, mainly divided into isolated word and continuous word speech recognition system, specific-person and non-specific-person speech recognition system, small vocabulary and large vocabulary speech recognition system, and embedded/server speech recognition system. In our lives, people's natural speech is based on the speaker's needs to add punctuation or break at the end of a sentence, and other parts can be pronounced continuously. In the early speech recognition, the isolated word phonetic system was mainly based on single characters or words [5]. According to the way the acoustic model is established, we can divide speech recognition into specific-person and non-specific-person recognition. Specific-person recognition means that the user must input a large amount of pronunciation data and train it before recognition. The non-specific-person system is that, after the system is established, the user does not need to input the training data in advance and can directly identify. Classification of speech recognition system is shown in Figure 1.

The research of speech recognition technology has a high degree of interdisciplinary nature, extensively involving the principles and methods of knowledge of multiple disciplines [6]. Using this comprehensive knowledge, we can summarize the principle of speech recognition technology as follows: Discrete symbols are used to represent human acoustic signals. The speech signal contains the semantics, grammar, and structure of the speaker's language, and the language information in the speech signal following the short-term amplitude spectrum is coded in the time variation mode [7].

Algorithm-based speech recognition block diagram is shown in Figure 2. The speech input in the figure is the original voice signal collected by the voice equipment; the preprocessing process mainly includes three aspects: sampling the input original voice signal, antialiasing band-pass filtering, and removing the noise impact caused by various aspects; the feature extraction process is mainly to extract the reflection in the voice [8]. The acoustic parameters of speaker's essential characteristics mainly include short-term energy, short-term average zero-crossing rate, linear prediction coefficient, and cepstrum. In the training stage, the feature parameters are processed to establish a reference model. In the recognition stage, after the same processing of the speech signal, the speech feature parameters are obtained, and the test template is generated, and then the test template is matched with the reference template according to certain discrimination rules (such as grammar and semantic rules), and the good reference template is obtained as the recognition result. Obviously, a good matching result is directly related to the quality of speech feature parameters, speech model, and matching template [9].

It is very important to establish a model that can describe speech features well in the research and application of speech recognition. Digital technology is used to simulate the generation of speech signal, and the mathematical model of speech signal is established. This model is a linear system; if one group of parameters is selected, the output of the system can have the desired speech properties. These parameters of the system are related to the process of speech generation. According to the analysis of speech organ and speech production mechanism, combined with signal processing theory, the mathematical model of speech signal can be represented by three submodels: excitation model, vocal tract model, and radiation model.

2.2. Basic Ant Colony Algorithm. Ant colony algorithm is a random search algorithm. In this algorithm, the solution of the problem is abstracted into a state transition sequence from the initial state to the target state in the discrete state space. The optimal solution of the problem corresponds to satisfying the optimal evaluation criterion of the state transition sequence. The pheromone intensity value on the path is the basis for the ants to carry out the state transition. After each ant in the group completes a search, the pheromone intensity on the path is updated according to their respective paths, so as to complete a group search [10]. The search process of the ant colony continues to loop and finally maximizes the path strength on the optimal transfer sequence, so as to obtain the optimal solution through the exchange of information and mutual cooperation between individual ants.

The mathematical model of the ant colony algorithm is described in detail as follows: First, a ants are randomly placed on b cities, each path between cities has an initialization pheromone $\delta_{ij}(0)$, and each ant has a state sequence record table l_u . It is used to record the cities that the ants have walked. Then, each ant makes a state transition randomly according to the state transition probability, and each

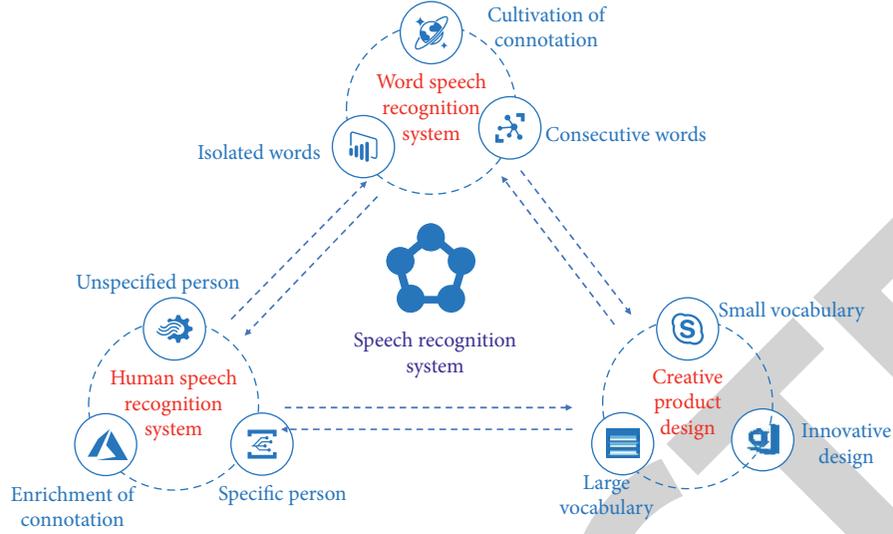


FIGURE 1: Classification of speech recognition system.

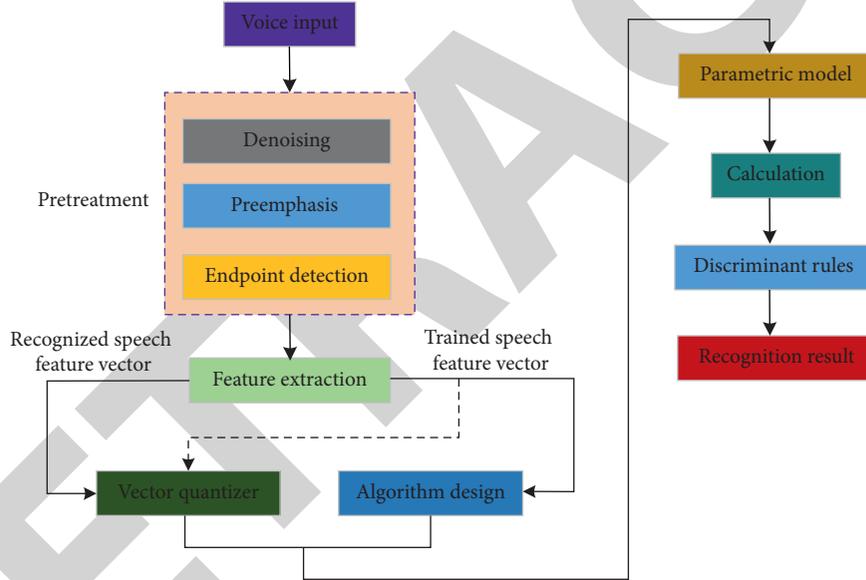


FIGURE 2: Algorithm-based speech recognition block diagram.

transition is only allowed to transition from the current state to an adjacent state, so the ant k transitions from the state ϑ_i . The state transition probability $\zeta_{ij}^k(t)$ to an adjacent state ϑ_j is defined as

$$\zeta_{ij}^k(t) = \begin{cases} \frac{[\delta_{ij}(t)]^\alpha \cdot [\xi_{ij}(t)]^\beta}{\sum_{\vartheta_j \in \ell_u} [\delta_{ij}(t)]^\alpha \cdot [\xi_{ij}(t)]^\beta}, & \vartheta_j \in \ell_u, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

As time goes by, the information left on the path will gradually disappear. We use the parameter $1 - \rho$ to indicate the degree of information volatilization. After n times, the ant completes a cycle. At this time, the amount of information on each path is

$$\delta_{ij}(t+n) = \rho \cdot \delta_{ij}(t) + \sum_{k=1}^m \Delta \delta_{ij}^k. \quad (2)$$

Among them, ℓ_u represents the city that ant k is allowed to choose to visit in the next step. Because the ant colony system has a memory function, it can record the city nodes that ant k has walked before, and the set will be dynamically adjusted with the evolution of ants. δ_{ij} represents the pheromone intensity on the path from city i to city j , $\Delta \delta_{ij}^k$ is the distance factor from city i to city j , α is the importance of the pheromone along the path, β is the importance of the heuristic factor, and both α and β are greater than zero.

2.3. Improved Ant Colony Algorithm. After analysing the basic principle of basic ant colony algorithm applied to time planning, the technical difficulty lies in how to use a series of

methods to increase the convergence speed of ant colony, find the optimal matching path between the test template and the reference template in the shortest time, so as to improve the recognition rate of the system, which directly determines the quality of the algorithm in the actual application process [11]. Therefore, this paper proposes an improved ant colony algorithm, such as a new ant colony state transition method, dynamic information request update rules, and better ant colony parameter selection, which effectively solves the template matching problem in dynamic time planning and achieves good results. Path analysis of improving speech recognition rate based on improved ant colony algorithm is shown in Figure 3.

2.3.1. Improvement of State Transition Selection of Ant Colony Algorithm. In the ant colony algorithm, each ant calculates the point that it should reach in the next step according to the state conditional probability formula. In the early stage of the algorithm, because the pheromone on each path is the same, the algorithm can only solve it according to the heuristic information, resulting in the solution speed to be slow, and after the information search is carried out to a certain level, the solutions found by all individuals are basically the same, and it is easy to fall into the local optimum prematurely [12]. In order to prevent the algorithm from falling into the local optimum solution, formula (3) is used for calculation:

$$\begin{cases} n = \arg \max\{\delta_{ab}(t)[\xi_{ab}(t)]\}, & \text{if } g < g_0, \\ p_{ab}^k = \frac{[\delta_{ab}(t)]^\alpha \cdot [\xi_{ab}(t)]^\beta}{\sum_{b \in \ell_u} [\delta_{ab}(t)]^\alpha \cdot [\eta_{ab}(t)]^\beta}, & b \in \ell_u \text{ else.} \end{cases} \quad (3)$$

g is a random number, g_0 is a constant on $(0, 1)$, when $g > g_0$, calculate the transition probability, and select point n according to the roulette rules. Through the change of this strategy, the algorithm can speed up the local optimization, increase the convergence speed by more than several times, and finally get the optimal value.

2.3.2. Dynamic Pheromone Update Strategy. The pheromone update strategy is one of the keys to determine the convergence speed. In the traditional algorithm, when the ant starts from an edge point far away from the moon point of the reference template, its path in the local area near the starting point is often better and it walks to the area closer to the reference template R point. The path is intricate and complicated, and the overlap with other ants' paths increases, the mutual influence increases, and the probability of taking a better path decreases [13]. Therefore, in order to avoid excessive accumulation of pheromone in the near area of point R , a dynamic pheromone update strategy is adopted, which stipulates that the pheromone left by each ant starting from a far distance should be gradually extended to the closer area of the ruler point. For attenuation, when you go to the farthest point, its pheromone should be minimized. For this reason, after each ant has walked an edge, the pheromone update is as follows:

$$\begin{aligned} \delta_{ab} &= (1 - \kappa)\delta_{ab} + \kappa\Delta\delta_{ab}^k, \\ \Delta\delta_{ab}^k &= \begin{cases} \sum_{i=1}^n \frac{\lambda}{h_n}, & \text{if: } n \in \text{allowed}, \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \quad (4)$$

Among them, Q is a larger constant, d_i is the length of the side that ant k has walked, and m is the total number of ants. This dynamic update strategy ensures the balance of the pheromone left by the ants, ensures the balanced contribution and mutual cooperation to the search, reflects the power of the group, and can greatly improve the convergence speed of the algorithm.

2.3.3. Using Adaptive Volatilization Coefficient. When other parameters are the same, the size of the pheromone volatility $1 - \rho$ has a great impact on the convergence performance of the ant colony algorithm. When $1 - \rho$ is very small, the residual information on the path dominates and the positive feedback of the information becomes relatively weak, and the randomness of the search is enhanced, so the convergence speed of the ant colony algorithm is very slow; when $1 - \rho$ is relatively large, the path searched before is likely to be selected again, which will affect the random performance and global search capability; therefore, regarding the choice of pheromone volatility $1 - \rho$ in the ant colony algorithm, two performance indicators, the algorithm's global search capability and convergence speed, must be considered comprehensively. In this paper, an adaptive method is used to change the pheromone volatility $1 - \rho$, the initial value of ρ ; when the optimal value obtained by the algorithm does not improve significantly within n cycles, q is reduced to

$$\theta(t) = \begin{cases} 9\varphi(v - 1), & \text{if: } \varphi_{\min} \leq 0.9(v - 1), \\ \varphi_{\min}, & \text{else.} \end{cases} \quad (5)$$

In this way, the possible amount of information on each path is limited to (q_{\min}, q_{\max}) , and the value beyond this range will be limited to q_{\min} or q_{\max} ; q_{\min} can effectively avoid the stagnation of the algorithm; q_{\max} one can avoid the situation that the amount of information on a certain path is much greater or less than that of other paths, so that all ants are concentrated on the same path, the algorithm is no longer diffused, and the convergence speed is accelerated [14–16]. Figure 4 shows the workflow of speech recognition based on improved ant colony algorithm.

2.4. Special Diagnosis Extraction of Speech Parameters. How to select the characteristic parameters of different speech is a basic problem to be solved in speech recognition system. The speech signal in speech recognition system includes the speaker's voice features and personality characteristics, and they are mixed together in a complex form [17, 18]. The extraction of speech feature parameters is to extract the parameters that can effectively represent the speaker's speech features, including the height of the formant frequency, the size of the bandwidth, the fundamental frequency, spectrum, and other parameters [19]. It is difficult to separate and extract these feature parameters

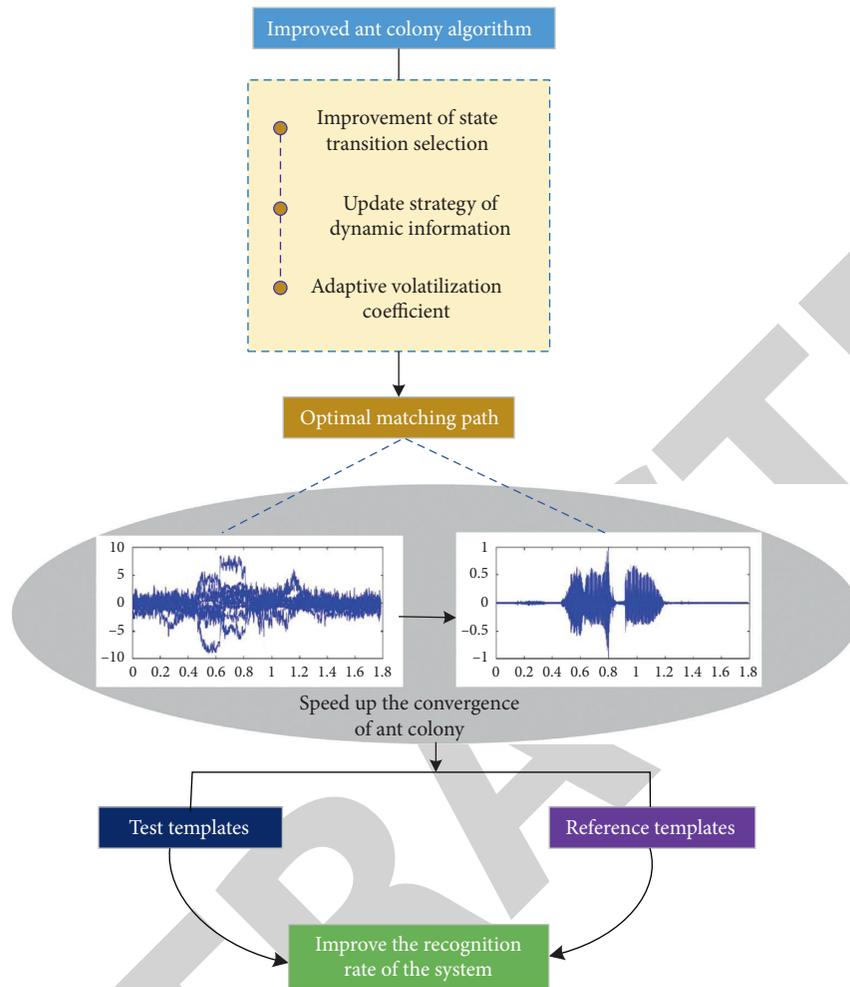


FIGURE 3: Path analysis of improving speech recognition rate based on improved ant colony algorithm.

accurately [20–22]. Based on the study of human voice mechanism and auditory perception of human ear, researchers have proposed a variety of speech feature parameters for speaker recognition, which mainly include the following categories [23–25]:

- (1) The characteristic parameters based on the mechanism of human ear are the short-term spectrum characteristics of speech, which mainly include pitch contour, formant frequency and bandwidth, voice strength, and its change. Because of the differences in the physiological structure of the vocal organs of different speakers and the fact that different speakers have different pronunciation habits, the short-term spectrum of speech is different, and it changes with time. Therefore, the parameters derived from speech short-term spectrum can reflect the speech characteristics of different speakers.
- (2) Based on the characteristic parameters of human auditory perception characteristics, we can analyse and obtain a variety of characteristic parameters, such as Mel frequency cepstral coefficient (MFCC) and perceptual linear prediction (PLP). These parameters have achieved good results in practical application.

- (3) Among these parameters, linear prediction analysis is one of the common techniques. Linear prediction coefficient (LPC) is consistent with the human vocal tract parameter model, which can effectively represent the full pole model. Therefore, it is more and more used in speech recognition system. Now, linear prediction coefficients and their derived parameters, such as linear prediction cepstral coefficient (LPCC), line spectrum pair (LSP), and autocorrelation coefficient, have been widely used in speech recognition system.
- (4) Hybrid feature parameter is a method to improve system performance by combining different and less correlated parameters. It has been widely used by researchers and has achieved good results.

3. Simulation and Application of Improved Ant Colony Algorithm in English Speech Recognition Accuracy

3.1. Simulation Test. In order to test the accuracy and practicability of the improved ant colony algorithm, the two

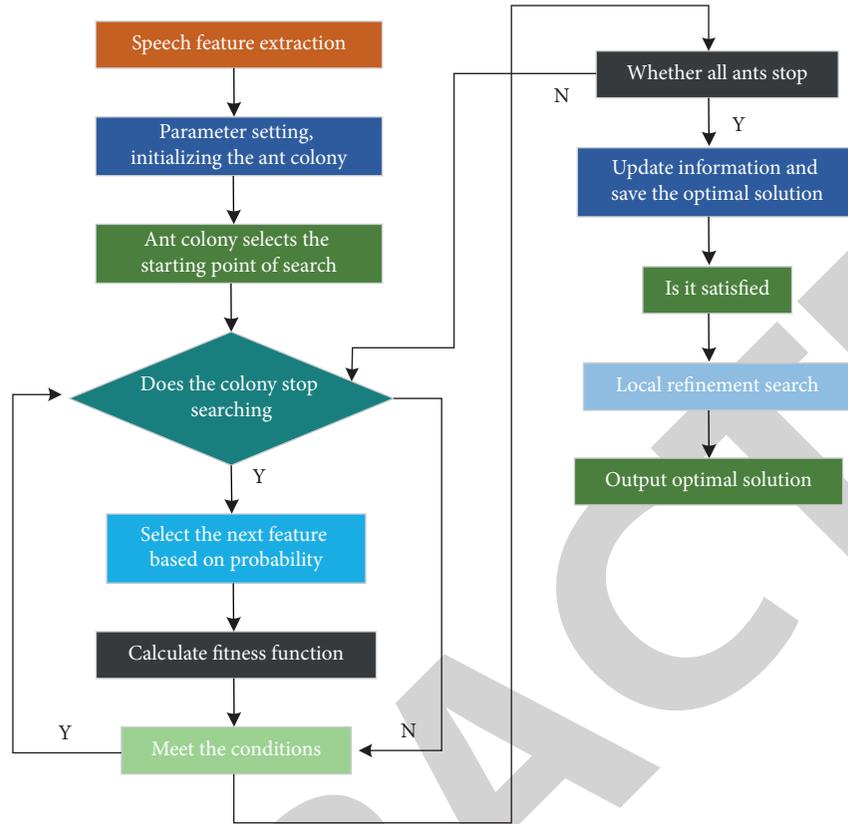


FIGURE 4: Workflow of speech recognition based on improved ant colony algorithm.

following typical test functions are selected to complete the verification.

3.1.1. Test Function 1

$$f_1(\theta, \sigma) = \frac{\sin(\theta_1)}{\theta_1} \frac{\sin(\sigma_2)}{\sigma_2}$$

$$-20 \leq \theta_i,$$

$$\sigma_i \leq 20, \quad i = 1, 2.$$
(6)

Figure 5 shows the three-dimensional surface graph of the function. Within the domain of definition, the global maximum value of this function is 1, and the best point is (0, 0).

3.1.2. Test Function 2

$$f_2(\theta, \sigma) = \theta_1^2 + \sigma_2^2 - \cos(18\theta_1) - \cos(18\sigma_2),$$

$$-20 \leq \theta_i,$$

$$\sigma_i \leq 20, \quad i = 1, 2.$$
(7)

Figure 6 shows the three-dimensional surface graph of the function $f_2(x)$. Within the domain, the global maximum value of the function is -2 , and the best point is (0, 0).

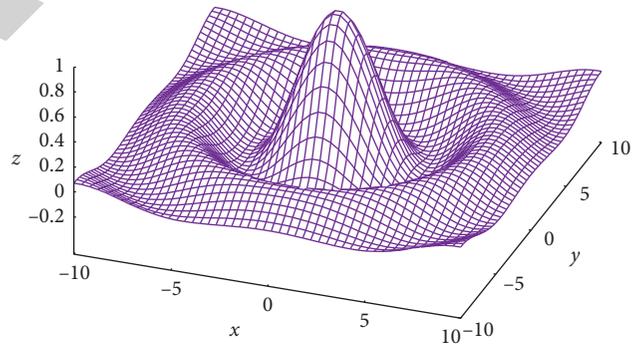


FIGURE 5: Simulated three-dimensional surface graph generated by test function 1.

3.2. Speech Recognition Experiment. The preemphasis parameters are used for signal framing using the Hamming window. The voice endpoint detection uses a combination of short-term average energy and short-term zero-crossing rate; after feature extraction in the pattern matching, the ant colony dynamic time planning algorithm is used for recognition, and finally the recognition result is obtained.

4. Experimental Results and Analysis

After completing the above preparatory work and related processing of speech signal, cepstral model is used to recognize and simulate the processed speech signal. According

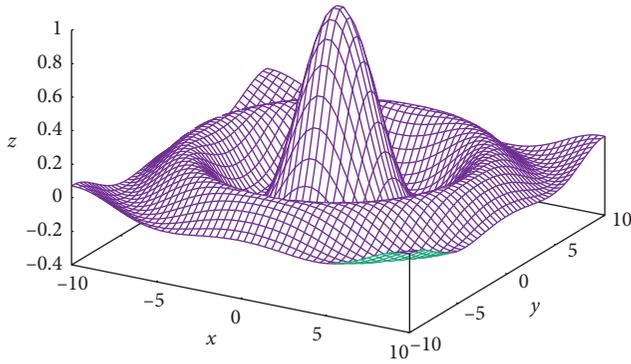


FIGURE 6: Simulated three-dimensional surface graph generated by test function 2.

to the flow chart of asdic optimized WNN in Chapter 4, the main experimental process of using WNN in speech recognition is as follows: (1) Preprocessing and feature extraction: The speech samples of the speech database are preprocessed: sampling and quantization, preemphasis, framing, and windowing. The sampling frequency is 16000 hz, the digital quantization is 16-bit, the frame length is 256 ms, the frame shift is 80 ms, and Hamming window is added. The feature parameters of the processed speech signal and 24 dimensional MFCC feature parameters are extracted. (2) The structure of wavelet neural network is determined: WNN is 40-10-10 structure. (3) Network training: The speech recognition template is trained, and the parameters of WNN are trained by asdic algorithm. (4) Identification of the speech to be tested: The steps are the same as (1). The extracted feature parameters are matched with the trained speech samples in the speech template library.

The experiment is completed on the platform of Windows 7 operating system, matlabr2016a. The experimental data composition is as follows: recording is in a quiet laboratory environment (no noise at this time, and the obtained voice data is pure sample), a total of 30 people, respectively, add different signal-to-noise ratios (SNR) (15 dB, 20 dB, 25 dB, and 30 dB), and the noise used in the experiment is additive Gaussian noise. Those people are 15 boys and 15 girls, each reads 100 words, and each word is repeated 30 times, for a total of 90000 words. In the experiment, the voice data were recorded in a natural and fluent voice dialogue. The training sample is the first 20 speech data samples of each word, and the test sample is the last 10 speech data samples. The parameters of ABC were set as follows: population number $S_n = 100$; maximum iteration times = 1000; limit = 50. In the experiment, the performance of WNN optimized by ABC is compared with WNN optimized by ACO and WNN optimized by GA. Among them, ACO algorithm's population number is 100; maximum iteration number is 1000; GA algorithm's population number is 100; maximum iteration number is 1000; crossover probability factor is 0.8.

4.1. Speech Recognition under Simple Vocabulary. First, the speech recognition rate of the improved ant colony algorithm is compared with the traditional algorithm. From Table 1 and Figure 7, it can be seen that the recognition rate

of the improved ant colony algorithm under the premise of different vocabulary is significantly higher than that of the traditional ant colony algorithm, and, for the improved ant colony algorithm under the premise of different signal-to-noise ratios, the recognition rate is significantly higher than that of the traditional ant colony algorithm, which significantly improves the antinoise performance of the system.

It can be seen from Figure 7 that additive noise reduces the recognition rate to a great extent. Even under the condition of SNR of 30 dB, the average recognition rate of the algorithm without any speech enhancement processing is 4.51% lower than that of pure speech, but the improved ant colony algorithm network still has a strong antinoise ability. In order to fully prove the effectiveness and accuracy of the improved ant colony algorithm, the improved ant colony algorithm is now compared with the swarm intelligence optimization algorithm model proposed by other authors. The parameter settings are as follows: the parameter setting of ABCs in the experiment is as follows: population number $S_n = 100$; the maximum number of iterations is 1000; the limit is 50. The population of ACO algorithm is 100; the maximum number of iterations is 1000; the population of GA algorithm is 100; the maximum number of iterations is 1000; the crossover probability factor is 0.8. The experimental results in Figure 8 are obtained, which fully verify the effectiveness and accuracy of the algorithm in this paper. Comparison of recognition rates of different algorithms is shown in Figure 8.

4.2. Speech Recognition under Different Classification Conditions. It can be seen from the above comparison results that the algorithm in this paper is better than the comparison algorithm in the recognition rate and recognition speed of speech recognition. However, in real life, due to various reasons such as dialects and the amount and continuity of vocabulary, the recognition rate of speech and recognition speed will be affected. In order to fully verify the effectiveness of this algorithm in speech recognition, the following experiments are carried out to compare different recognition methods under different classification and recognition objects.

It can be seen from Figure 9 that the recognition rate of the traditional ant colony algorithm has increased to a certain extent, but it is still lower than the recognition rate of the improved ant colony algorithm. In a word, the recognition rate of the improved ant colony algorithm is higher than the other three algorithms under different classification conditions, again verifying the effectiveness of the algorithm in this paper.

5. Discussion

In terms of recognition rate, the improved ant colony algorithm and the traditional algorithm are ideal for the recognition of command words, especially for a single command word for a specific person. In the experiment of speaker-independent recognition rate, the improved ant colony algorithm has a slightly higher recognition rate

TABLE 1: Comparison of speech recognition rate with different signal-to-noise ratio and vocabulary.

Number of words	Algorithm	Signal to noise ratio (dB)				
		15	20	25	30	Clean
10	Traditional algorithm	88.39	88.83	89.67	90.25	90.78
	Improved ant colony algorithm	94.15	95.08	95.52	96.88	98.82
20	Traditional algorithm	87.62	87.81	88.24	89.03	89.82
	Improved ant colony algorithm	93.73	94.50	95.23	96.96	98.29
30	Traditional algorithm	87.41	88.53	89.41	90.03	90.12
	Improved ant colony algorithm	92.53	93.41	94.74	96.18	97.69
40	Traditional algorithm	87.85	88.38	89.76	90.62	91.54
	Improved ant colony algorithm	90.17	93.80	94.53	95.86	97.12
50	Traditional algorithm	86.62	87.16	88.13	88.84	90.42
	Improved ant colony algorithm	92.57	93.85	94.48	95.86	96.83

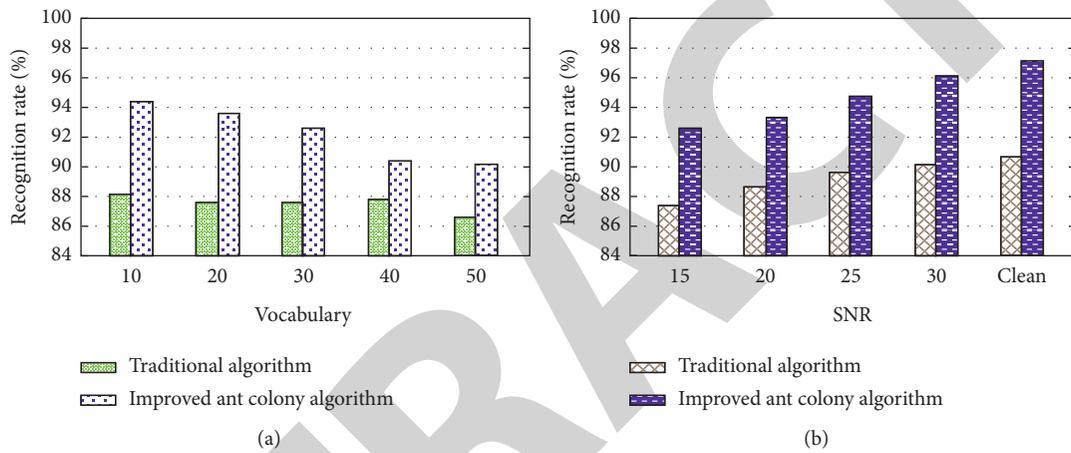


FIGURE 7: Comparative analysis of recognition rate under different conditions. (a) Recognition rate under different vocabulary size. (b) Recognition rate under different SNR.

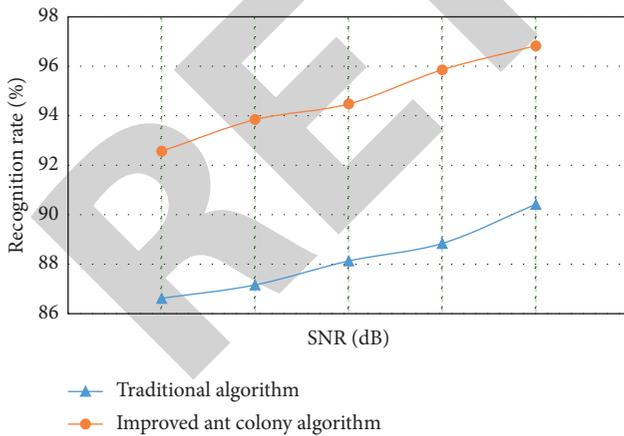


FIGURE 8: Comparison of recognition rates of different algorithms.

compared to the traditional algorithm. Although the gap is not big, for the simple isolated word recognition system, this gap has been a relatively large advantage. For continuous speech recognition, the recognition rate is slightly lower than that of isolated words. The recognition rate of the traditional algorithm is less than 95% in the continuous speech

experiment. In this aspect, ant colony dynamic time planning algorithm has better performance compared to DTW, especially in speaker-independent continuous speech experiment. The more complex the situation is, the better the performance of the improved ant colony algorithm is, which is also because the improved ant colony algorithm has to carry out 20 iterations each time when calculating the global average distortion, and each iteration keeps updating pheromone. The final optimal path can more accurately represent the similarity between voice signals compared to DTW algorithm, which reflects the superiority of this algorithm. On the other hand, the improved ant colony algorithm has potential, and the speech recognition system based on the improved ant colony algorithm is expected to further improve the recognition rate in complex situations. We need to do more experiments to further study the parameters of the corresponding ant colony algorithm and improve the pheromone update mechanism of the ant colony algorithm to find a more reasonable and reliable ant colony algorithm model. In the process of experiment, we also notice that the environment adaptability of speech recognition system is not enough when the experimental conditions are changed. It is mainly reflected in the strong dependence on the environment; that is, the speech to be

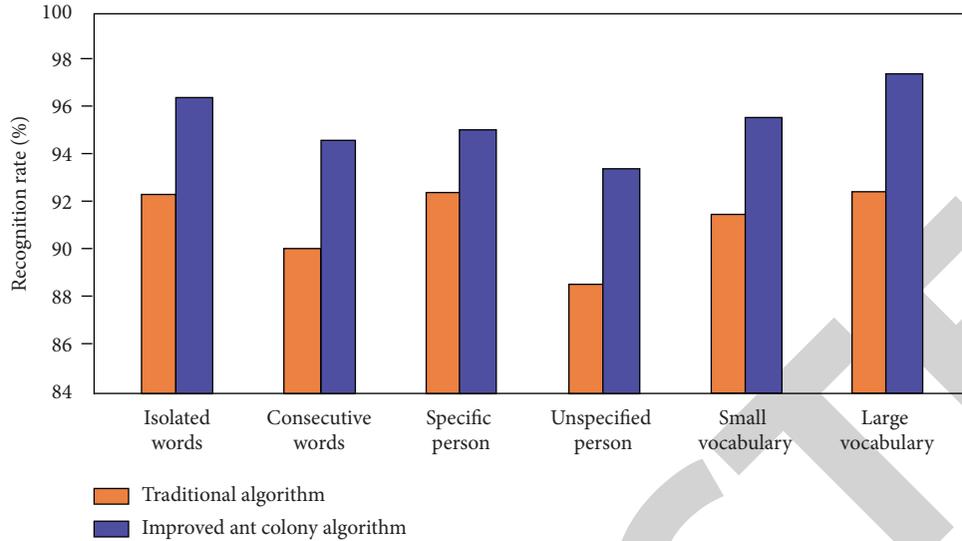


FIGURE 9: Comparison of algorithm recognition rate under different classification conditions.

tested and the speech to be trained should be obtained in the same environment; otherwise, the recognition rate of the system will decline. For example, we use different environments to do speaker-specific continuous speech recognition experiments. One part of the same female voice was collected in the laboratory, and the other part was collected in the school square through a notebook. The results of this experiment are not consistent with those obtained in the same environment.

Of course, this has nothing to do with the measure estimation algorithm, because both ant colony dynamic time algorithm and traditional algorithm have this situation, and the problem is not in this area. This is about the adaptability and antinoise performance of the system, and the improvement in this aspect will be completed in the next work. Although the recognition rate of the improved ant colony algorithm is higher than the traditional algorithm, its recognition speed is slightly slower than the traditional algorithm. In the experiment of speaker-independent Chinese continuous speech recognition, it takes about 2 seconds to recognize a pattern to be tested, while the conventional algorithm takes about 1 second. This can be explained from the time complexity: the time complexity of the traditional algorithm is $O(n^2)$, in which n is the length of feature vector sequence of the reference template and the template to be tested, respectively; in terms of the time complexity, the ant colony dynamic time planning algorithm is slightly slower than the traditional algorithm, but the gap is only linear and does not reach the exponential level. Therefore, we can conclude that the improved ant colony algorithm is completely feasible, and the small gap in speed can be made up by relatively fast processor in practical application; moreover, we can improve the ant colony algorithm to make it more efficient, which needs further research. In terms of space complexity, the conventional algorithm needs $2 \times m \times n$ spatial storage frame matching distance matrix and cumulative distance matrix, so the

space complexity of the whole algorithm is $O(n^2)$. This is similar to the traditional algorithm. It can be seen that the spatial complexity of the basic ant colony algorithm on data storage is simple and easy to implement. In speech recognition system, the improved ant colony algorithm is a good method. Through the above analysis of recognition rate, system adaptability, operation speed, algorithm time complexity, and space complexity, we can conclude that the improved ant colony algorithm is an intelligent optimization algorithm that can replace the traditional algorithm in speech recognition system, and this algorithm is still very large in speech recognition system by optimizing the parameters of ant colony algorithm and improving pheromone update mechanism of ant colony algorithm; its performance in speech recognition system can be further improved. These tasks will be further completed in future work.

6. Conclusion

Based on the application of ant colony algorithm in speech recognition, this paper proposes a series of improvement strategies, which can effectively improve the convergence speed of the basic ant colony algorithm and overcome the defect that the algorithm is easy to fall into the local optimal solution. Combined with the dynamic time planning algorithm, the improved ant colony dynamic time planning algorithm is successfully applied to the speech recognition problem and has achieved good results. The results show that the improved ant colony algorithm can find a better scheduling strategy in a short time, improve the global search ability and accuracy of ant colony, and effectively improve the efficiency of speech recognition system.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this paper.

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