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Oral English Recognition Teaching System Based on Natural Language Processing and Emotional Analysis

Weitang Li*

Department of Foundation Course Teaching, Shaanxi Energy Institute, Xianyang, Shaanxi 712000, China

The HMM model is widely used in speech recognition systems because of its high efficiency and good stability. It contains observable sequence and hidden state sequence. It is a process of finding the optimal hidden state sequence by means of an observable state set and characteristic parameters. In this paper, the author designs an oral English recognition teaching system based on natural language processing and emotional analysis. The system chooses several functions which are suitable for mobile terminal development, and provides users with basic modules for learning and practicing spoken English, including speech recognition, voice assessment, spoken broadcast and spoken dialogue. Although the endpoint detection algorithm has been used to remove certain white noise, it has not completely eliminated the noise, and the speech recognition rate has been affected.

Keywords: Natural language processing; Emotional analysis; Oral English recognition; Training system

1. INTRODUCTION

Nowadays, economic globalization has led to many and frequent exchanges occurring in countries all over the world, and the fact that English Is an International used global language as envisaged for, has engendered great enthusiasm for the learning of the English language (Dorothy et al., 2017; Miles et al., 2017). More and more people in non-English-speaking countries are eager to acquire a more comprehensive range of English skills beyond mastering just the necessary vocabulary and grammar. Many people now want to be able to express themselves orally in English. Hence, it is also very important to improve the effectiveness of English teaching and learning. Therefore, the methods used for the teaching and learning of English in non-English-speaking countries have become a hot topic of discussion and research. In fact, the acquisition of competent listening, speaking, reading and writing skills in English takes a lot of time and energy. Therefore, these four abilities are not taught to students one by one in the classroom (Niolak et al.,2017). Under the situation that there already not enough English teachers, teachers often focus only on teaching reading and writing (Julio, 2018), neglecting the oral component of English language acquisition. Therefore, it is not easy for students from non-English-speaking countries to acquire and master these four skills at the same time.

When traditional teaching methods cannot meet the needs of oral English teaching, with the continuous innovation of computer science and technology over time, English learning is no longer confined to the single classroom. Intelligent autonomous English learning will become a trend (Muslem & Abbas, 2017; Mawson, 2017). Today, with the rapid development of speech recognition technology and other multimedia technologies, computer-aided language learning (CALL) has gradually begun to meet the broader needs of language learners (Basic et al., 2017). Similar to pronunciation evaluation systems based on speech recognition technology, CALL has become the focus of many researchers.

Current computer-aided language learning systems focus mainly on the learning of vocabulary and grammar. The

*Corresponding author: Weitang Li, Email:liweitang68@163.com

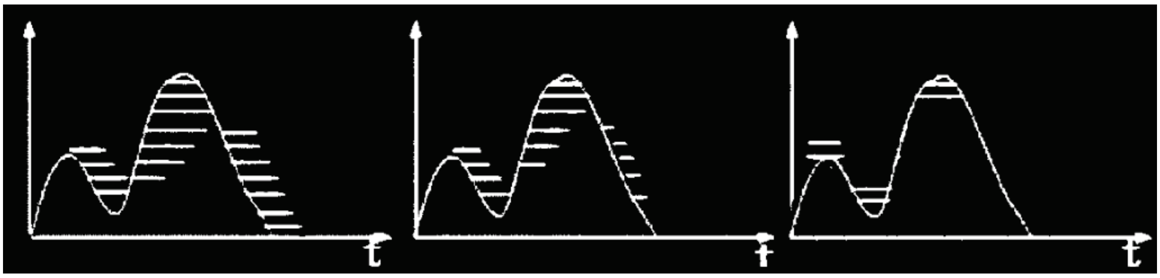

Figure 1 Pattern matching diagram.

only oral English learning software has a single function, which can give learners only an overall pronunciation score (Pingkuo & Zhongfu, 2016; Schleich et al., 2017). However, due to their own limitations, it is difficult for self-learners to find errors and correct their pronunciation by themselves. Software that offers a pronunciation-correction function can help learners to correct pronunciation errors in time before they become habits (Sun et al.,2014; Zhou et al., 2017). The spoken English teaching system based on emotion and emotion analysis technology mainly uses speech recognition technology to calculate learners' pronunciation scores and detect pronunciation errors. The system uses two parts of the CMU open-source item SPHINX 3.5 phoneme recognizer all phone and linker align (Kabalci, 2016; Salem et al., 2017). The assessment of learners' pronunciation must have a benchmark. Trained speech models can be used as scoring criteria. When the model is complete, many sentences can be scored. Scoring is generally done by comparing the user's voice with the benchmark model.

Researchers have tended to rely heavily on the most well-known systems including: IBM's Via Voice and Dragon System's Naturally Speak in, Nuance's Nuance Voice Platform, Microsoft's Whisper, Sun's Voice Tone, etc. (Liu & Zhou, 2015). Moreover, in the developed countries of the western economy, a large number of speech recognition products have entered the market and service fields. For example, some users' telephones and mobile phones already have voice recognition dialing functions, and some voice memos and smart voice toys are also embedded with voice recognition and voice synthesis. In addition, people can also find air tickets, banks, and travel information in the dialogue system through voice recognition in the telephone network. According to statistics, more than 85% of users are satisfied with the performance of such functions.

2. RESEARCH METHODS

2.1 Traditional Scoring Algorithm

The requirements for the scoring algorithm are that it: (1) has better reliability and consistency with expert ratings; and (2) reflects the learner's ability to pronounce and does not accept only the best similarity between it and the standard pronunciation.

Research has found that the HMM-based phoneme posterior probability algorithm is very stable and not easily affected by the individual characteristics of the learner or the changes of the sound channel; moreover, it provides better feedback on the similarity between the learner's pronunciation and the standard pronunciation (Hu et al., 2013; Diamantoulakis et al., 2015).

During speech processing, input features and templates cannot be compared directly because the speech signal is very random. Even if the same person reads the same sentence, it is impossible to do so within exactly the same amount of time (Ferrer et al.,2010; Irfan et al.,2017). For example, as the vocalization speed increases, the length of time of the vowel sportion will be shortened, while the length of the consonant or transitional sound portion remains substantially unchanged. Therefore, time regulation is essential. Dynamic time warping is a nonlinear regularization technique that combines regular time with distance calculation. Hypothesis: The feature vector sequence of the reference template is $a_1, a_2, \cdots, a_m, \cdots, a_M$, and the sequence of feature vectors of the input speech is $b_1, b_2, \cdots, b_n, \cdots, b_N$, and $b_1, b_2, \cdots, b_n, \cdots, b_N$. Thus, dynamic normalization is to find a time warping function $m = w(n)$ that nonlinearly maps the time axis n to the reference template time axis m, such that:

$$D(n, w) = \min_{w(n)} \sum_{n=1}^{N} d[n, w(n)] \tag{1}$$

In the above formula, $d[n, w(n)]$ represents the distance between the feature vector of the nth input and the $w(n)$ reference template vectors. Obviously, $w(n)$ should be a non-decreasing function. In time, dynamic time aligns with the input features and reference template features to eliminate any unnecessary differences between the two. Figure 1 shows a schematic diagram of the magnitude of the distortion between linear matching and nonlinear matching, direct matching (Ferrer et al.,2005; Guerbai et al., 2015). The nonlinear matching method shown in the figure is likely to minimize the non-essential difference between the two modes.

Dynamic time warping is an optimization problem. A common dynamic programming technique for solving this problem takes advantage of the concept that local best produces an overall optimal value. The goal of the solution is to find the optimal time warping function $w(n)$ and the corresponding $D(n, w)$. In some specific problems, the DTW function satisfies the following conditions.

Boundary conditions:

$$w(1) = 1, w(N) = M \tag{2}$$

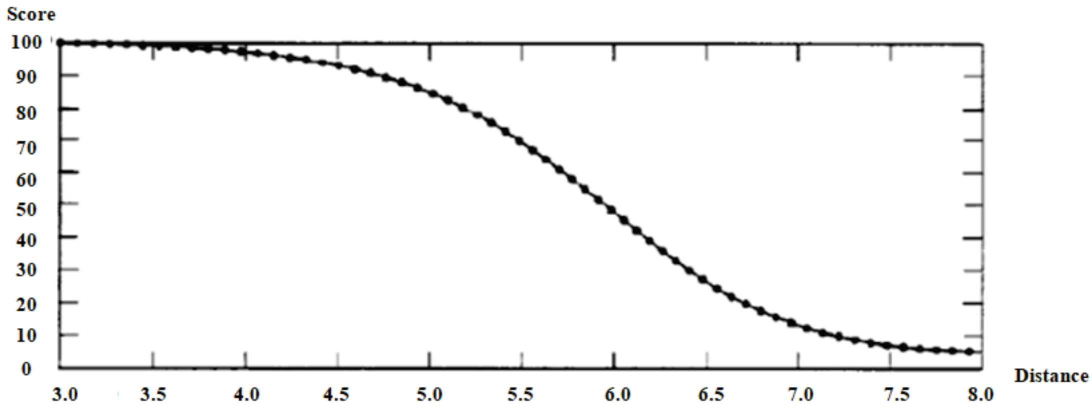

Figure 2 Distance-score conversion chart.

Continuous conditions:

$$w(n+1) - w(n) = \begin{cases} 0, 1, 2 w(n) \neq w(n-1) \\ 1, 2 w(n) = w(n-1) \end{cases} \tag{3}$$

A recursive formula can be introduced:

$$D(n+1, m) = d[n+1, m] + \min[D(n, m)\, g(n, m), D(n, m-1), D(n, m-2)] \tag{4}$$

Among them:

$$g(n, m) = \begin{cases} 1 w(n) \neq w(n-1) \\ \infty w(n) = w(n-1) \end{cases} \tag{5}$$

Since the calculation of each $D(n+1, m)$ requires the calculation of the D values of the three points in the n columns, the use of dynamic programming techniques is very time consuming when calculating time warping. Pattern recognition often calculates the distance between features. In speech recognition, the degree of similarity between the reference mode and the input mode is determined by the degree of distortion between the frames that make up the two. It is a measure that reflects the difference in signal characteristics and is expressed as $D(x, y)$. This is the applied distance measurement method that needs to satisfy the following mathematical properties:

(1) Positive value: $D(x, y) \geqslant 0$. When $x = y$, there is $D(x, y) = 0$.

(2) Symmetry: $D(x, y) = D(y, x)$

(3) Triangle $D(x, y) \leqslant D(x, z) + D(z, y)$ inequality:

When calculating the DTW distance, the absolute average distance is used:

$$D(x, y) = \frac{\sum_{i=1}^{N} |x_i - y_i|}{N} \tag{6}$$

DTW distances are not directly categorized as pronunciations, and a reasonable mapping from distance to score must be sought. Assuming that the relationship between distance and score satisfies the formula:

$$score = \frac{100}{1 + a\,(dist)^b} \tag{7}$$

Obviously, this formula can map distances within a range of 0 to 100. According to this, the distance-score conversion is shown in Figure 2 below.

When solving the unknown parameters, a and b in the formula, we need to know some score and distance pairs. These parameters can be solved by the scores of some experts in the experiment and the DTW distance. When using the formula of this paper, even if the distance is larger or smaller than the test, the score can be reasonably converted to the range of 100 to 0. Since the two feature parameters are used, the actual score estimation formula is slightly complicated, and the final score is the weighted sum of the two.

$$score = w_1 * \frac{100}{1 + a_1\,(dist_1)^{b_1}} + w_2 * \frac{100}{1 + a_2\,(dist_2)^{b_2}} \tag{8}$$

The parameters in the formula satisfy these constraints: $a_1, a_2, b_1, b_2 > 0, w_1 + w_2 = 1$. a_1, a_2, b_1, b_2 is the parameter of the distance component, and w_1, w_2 is the weight of the three features.

2.2 HMM-based scoring method

As shown in Figure 3, this is the system's scoring system process. The standard answer is based on the pre-trained acoustic model and tone model. Speech recognition technology is used to find the difference between the test speech and the model and combined with the scoring mechanism to give a score. The feature parameter extraction mainly includes two characteristic parameters: the fundamental frequency trajectory and the Mel cepstral parameter, which are used as the characteristic parameters of tone recognition and sound recognition respectively. The use of ViterbiDecoding first divides the speech signal into a single syllable. Then, the sound model and the tone model are compared for each syllable, and the recognition results are combined with our pre-designed scoring mechanism to convert the scores, that

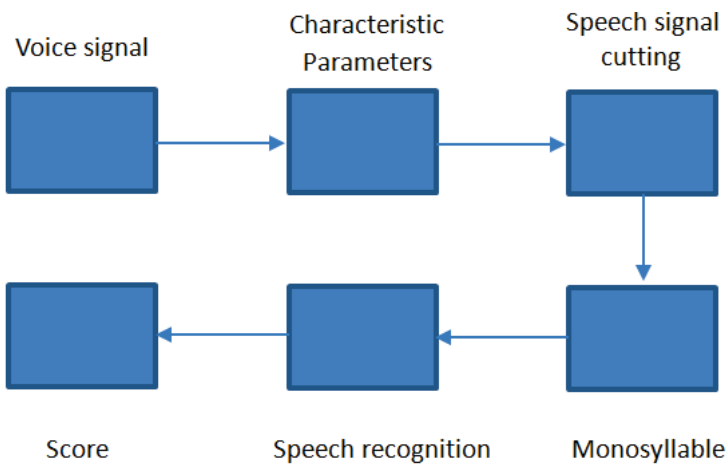

Figure 3 Schematic diagram of the scoring system.

is, the scores of the test speeches. This scoring system includes the Hidden Markov Model (HMM), the TreeNet and the Viterbi Algorithm, which are commonly used in speech recognition. In terms of tone recognition, Chebyshev Approximation, Orthogonal Expansion, K. means grouping, and class design are included.

There is a difference between the HMM method and the DTW method. The HMM pattern library is not a pre-stored pattern sample, but a set of H/VIM model parameters with the highest probability of combining with the training output signal formed by repeated training and the iterative algorithm (Baum - Welch). A is the state transition probability distribution matrix, and B is the system output probability distribution matrix. The parameters reflect the numerical parameters of the statistical properties of the training speech process, not the mode feature parameters themselves. HMM-based scoring is a statistical model-based approach that differs from DTW algorithm template matching.

The HMM-based method is mainly used for the scoring of phonemes. The more common methods are the scoring of log likelihood and the scoring of logarithmic posterior probability. Unlike feature comparison scores, this method indicates the learner's ability to pronounce a language, not just the difference between a standard speaker individual.

For the log likelihood score, the formula is defined as follows:

$$S_i = \sum_{t=\tau_j}^{\tau_{t+1}} 1g\left[P\left(q_t \mid q_{t-1}\right) P\left(o_t \mid q_t\right)\right] \tag{9}$$

Among them, o_t and q_t are the observation vector and the state of HMM at time t, respectively. If the definition of the model is $\lambda = (M, N, A, B, \pi)$, $P\left(q_t \mid q_{t-1}\right)$ is the state transition probability, that is, A in the HMM model. Among them, $P\left(o_t \mid q_t\right)$ is the probability distribution matrix of the observation vector, that is, B in the HMM.

The scoring method for scoring sentences is:

$$S = \sum W_i S_i \Big/ \sum W_i \tag{10}$$

Among them, S is the sentence score, Log likelihood scores can be used for both text-related and text-independent situations. After analyzing the characteristics of several pronunciation algorithms, the system uses the HMM-based phoneme posterior probability algorithm as a reference for the pronunciation evaluation algorithm.

The score based on the HMM posterior probability is:

Among them, $P\left(O_t \mid q\right)$ is the probability distribution of the observation vector O_t under the phoneme q, and $P(q)$ is the prior probability of the phoneme q. The sum on the denominator is the sum of the phonemes $q = 1, \cdots, M$ that are independent of all the text.

The phoneme q_i takes the logarithm of the posterior probability of each pause in the i-th segment of speech, and then the obtained values are accumulated to obtain the logarithmic posterior probability score of the phoneme q_i under the i-th segment of speech:

$$P_i = \sum_{t=\tau_j}^{\tau_{t+1}} 1g\left[P\left(q_t \mid o_t\right)\right] \tag{11}$$

Because beginners' utterances tend to be slow, the speech rate is also a factor that affects the pronunciation score. The formula for the definition of the phoneme duration is:

$$D = \frac{1}{N} \sum_{i=1}^{N} 1g\left[P\left(f\left(d_i \mid q_i\right)\right)\right] \tag{12}$$

d_i is the duration of the i-th segment of phoneme q_i and is a normalized function. Taking into account the independence of text and scholars, the speech rate (ROS) metric is used to normalize the speech duration. ROS is the number of phonemes per unit of time in a sentence or speaker's utterance, which is usually taken as $f(d_i) = ROS * d_i$.

Under normal circumstances, the novice English practitioner's speech postponement probability score will be lower than that of the professional English-speaking teacher for training. This rating reflects to some extent certain errors in non-native English speakers' pronunciation.

2.3 Error detection

After the MFCC feature value is subjected to the forced correlation recognition and scoring process of the phoneme,

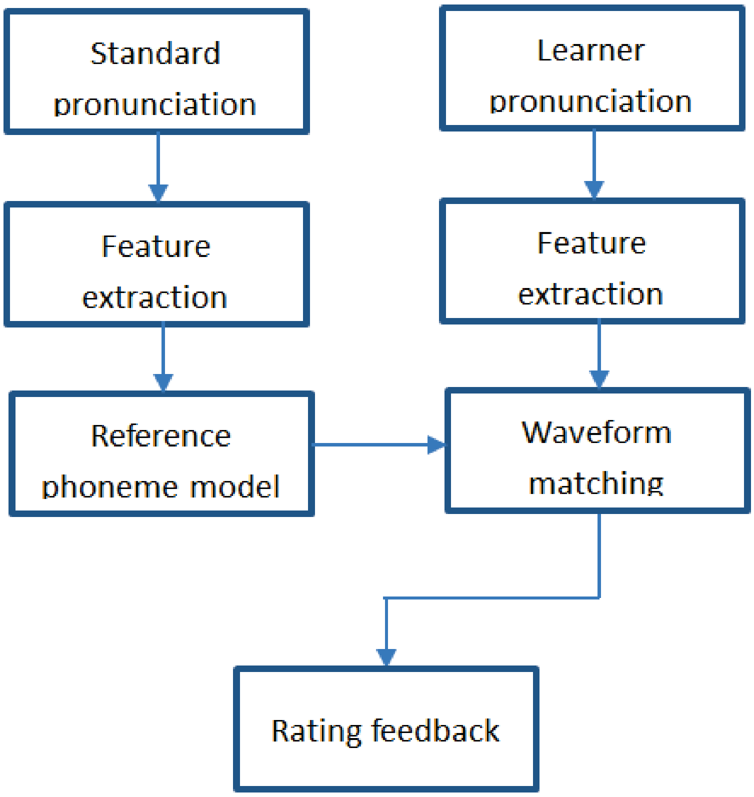

Figure 4 Schematic diagram of the speech recognition module.

the corresponding associated phoneme string, phoneme start-time and end-time scores are obtained. After these results are obtained, the phoneme error detection process is started.

According to the results of the most similar phoneme judgment, the phonetic reading errors are roughly divided into three categories: misreading, missing reading, and adding phonemes. The most similar phoneme is defined as the phoneme with the highest HMM likelihood:

$$q_i = \arg Max\,[L_i\,(q)] \tag{13}$$

$L_i\,(q)$ is the likelihood of any one of the factors g in the i period:

$$L_i\,(q) = P\,(q\,|Q_i\,) = P_i = \sum_{t=\sigma_i}^{\sigma_{i+1}-1} 1g\left[P\,(s_t\,|s_{t-1}\,)\,P\,(o_t\,|s_t\,)\right] \tag{14}$$

Missed phoneme: The tone of q_i is not sent.

$$q_i = \begin{cases} q_i \\ q_{i+1} \\ SIL \end{cases} \tag{15}$$

Misreading phonemes: The pronunciation of q_i is incorrect and sounds more like other pronunciations. This is expressed as $q_i \neq q_i$ and is not a missed phoneme error.

Add phoneme: The recognition result contains extra phonemes. The results obtained by the correlator cannot distinguish between these three types of errors. Among them, the error detection module can locate only the wrong phoneme according to the phoneme score. For further research, it is necessary to obtain the identified phoneme result through the recognition process to determine which kind of error is specific. For different needs, we can design two methods of error detection.

If the type of error detection is not required, we first use the correlator to score the evaluation voice to correlate the phoneme level and set the threshold. When the corresponding phoneme score is below the threshold, the phoneme is considered to be a wrong phoneme. If a specific type of error needs to be detected, an additional phoneme recognition process is required.

3. SYSTEM DESIGN

The modules of the speech recognition system mainly include five parts: feature value extraction, phoneme recognition, phoneme association, pronunciation evaluation and error detection. Finally, the system will give the learners effective feedback in terms of pronunciation scores and corrective advice. This learning method enables learners to better understand the pronunciation errors and correct them to improve their oral skills. The speech recognition module is shown in Figure 4.

External function: Implement a visualization window. Example library view: Follow the specified example or learning strategy during playback. Information view: Display sentences and phonetic symbols; display single phoneme scores and corrections; display sentence prosody scores and corrections, play corrections. User Management Interface: Display user's vocabulary, learn files, analyze misreading phonemes and common mistakes. The system recognizes

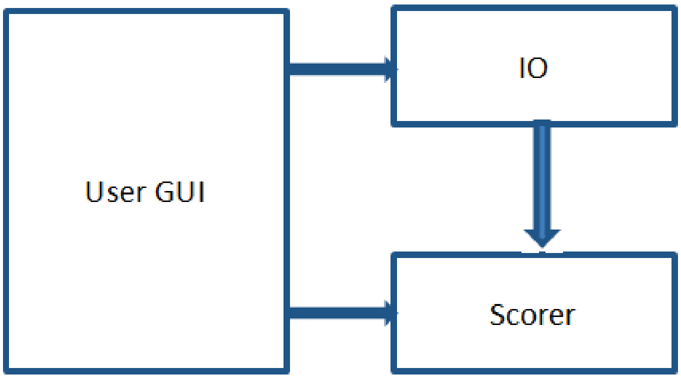

Figure 5 Relation chart of system module diagram.

Figure 6 Renderings of interface.

Table 1 Phoneme correlation results.

time	phoneme							
	g	u	d	SIL	t	u	s	i:
Start time	22	28	35	38	46	51	65	76
End Time	27	34	37	45	50	64	75	89

English learners with a strong Chinese accent. The system designed in this paper is implemented by C ++ programming and runs on the Windows platform. A small part of the system is written in MATLAB. Specific requirements are as follows: (1) the occupied memory space is small; (2) the limitation of the operating system to the operating system is limited; (3) the realization of English-based El training system based on HMM under VC platform needs to properly consider the scalability of the system itself and the friendliness of the interface; and (4) the system can give a particular user a pronunciation-matching score, and finally provide feedback that will help the user to improve his/her oral English skills.

In the voice processing diagram depicted in Figure 4, the system is divided into three parts: user interface GUI, input/output I/O, and Scorer. The system module relationship is shown in Figure 5 below.

The main interface design effect is shown below in Figure 6.

4. ANALYSIS AND DISCUSSION

There are many ways to classify pronunciation errors. According to the recognition results of phoneme recognizer, phoneme reading errors can be simply divided into two categories. 1) Mispronunciation of phonemes. There is no expected phoneme Qi in the result of phoneme recognition of Qi related segment, but silence. 2) Adding phonemes. There are redundant phonemes in the recognition results of phoneme correlation segments. Based on a two-pass process of compulsory association-phoneme recognition, we can design methods to detect the three afore mentioned errors. The results of association and recognition (the first three word parts) and error detection of a sample sentence "Good to see you again" are shown in Tables 1 and 2. The start and end times in the table are indicated by the serial number in the short-term analysis window. The window length is 25ms and the step length is 10ms. SPHINX3 align is used in Viterbi mandatory association, and the input comprises voice features and text. Phoneme recognition is accomplished with SPHINX3 all phone.

Error detection has a good effect on misreading or missing phonemes. However, for inserting phonemes, the detection error rate is higher. In the error detection result of the verification corpus, there are 712 misread phoneme errors and 653 missing phonemes. The statistics for the most difficult to read and the easiest to read wrong phonemes, are shown in Table 3. Each line lists one phoneme that was misread and the three phonemes that are most easily mispronounced.

Table 2 Phoneme recognition results.

time	phoneme									
	g	ə	d	SIL	t	ə	n	t	θ	i:
Start time	21	29	32	37	45	52	59	64	69	74
End Time	28	31	36	44	51	58	63	68	73	92

Table 3 The least pronounced and most pronounced phonemes.

Mispronounced phonemes	Accuracy rate /%	Mispronunciation rate%		
k	90.34	t(2.36)	p(1.63)	g(1.27)
i	88.58	I(2.75)	∧(1.47)	eI(1.28)
n	81.49	ŋ(2.77)	d(1.96	m(1.73)
t$\int$	38.55	t(20.48)	dʒ(12.04)	d(6.02)
$\int$	34.85	Z(12.44)	s(12.0	dʒ(9.12)
ɔI	31.69	əʊ(23.07)	∧ (11.53)	I(7.69)
aʊ	30.34	ɔ: (13.79)	p(13.79)	∧(7.58)

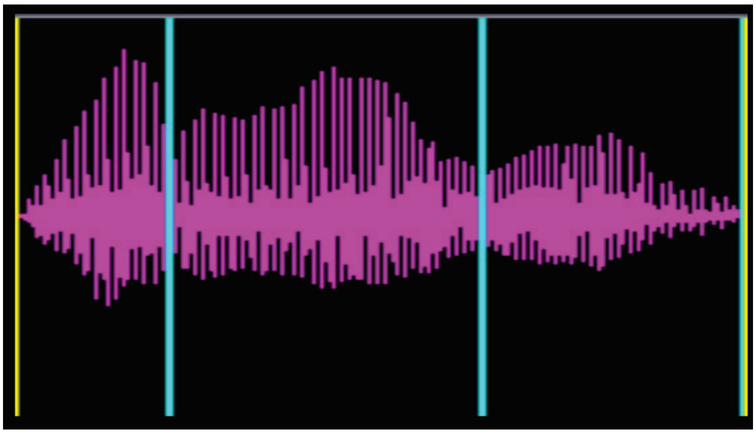

Figure 7 Speech segmentation effect map after boundary modification.

The evaluation of speech quality is not related only to the disciplines of linguistics, phonetics, signal processing, but also to science, psychology, and even cultural traditions. It is a rather complicated aspect of human communication. The method used to evaluate speech quality is based on both subjective and objective scoring. There are many common scoring methods including: distortion average opinion score, average opinion score, diagnostic rhyme test method, judgment satisfaction test method, to name a few. The shortcoming of the subjective scoring of speech is that it is time-consuming and laborious, and because of the limitations of many test conditions and the subjective characteristics of the testers, the reliability of the test results is affected to some extent. Therefore, the objective evaluation of the quality of speech usually requires some equipment, which is flexible and is not affected by actual conditions and artificial factors. At the same time, we can directly compare test results at different times and different occasions. To date, many methods have been developed for evaluating the quality of pronunciation. Our commonly used methods are: score based on the HMM log similarity, score based on the dynamic time regular DTW, and score based on the HMM logarithm posterior probability, segment time score, segment classification score, fluency score and other methods. These scoring methods involve standard matching of various effective similarities according to the standard pronunciation as a benchmark.

DTW is an optimization algorithm. In order to align its features with those of the template, the time axis of the speech signal to be recognized is unevenly warped and curved, and the matching path between the two vector distances is calculated directly. Therefore, the earliest and most common method used to successfully solve the speech pattern matching problem is to obtain the regularization function with the smallest accumulation distance when the two vectors match. The disadvantages of the DTW method are that the amount of computation is large, the number of endpoint detections of the speech signal is too large, and the timing dynamic information of the speech signal is not sufficiently utilized.

As stated earlier, the requirements for the scoring algorithm are that it: (1) has better reliability and consistency with expert ratings, and (2) reflects the learner's ability to pronounce and does not accept only the best similarity between it and the standard pronunciation.

After research, it is found that the HMM-based phoneme posterior probability algorithm has very good stability and is not easily affected by the individual characteristics of the learner or the changes of the sound channel and gives better feedback on the similarity between the learner's pronunciation and the standard pronunciation. The modules of the speech recognition system comprise five main parts:

feature value extraction, phoneme recognition, phoneme association, pronunciation evaluation and error detection. Finally, the system will give the learners valuable feedback in terms of pronunciation scores and corrective advice. This learning method enables learners to better understand the pronunciation errors and correct them to improve their oral skills.

5. CONCLUSION

The error detection method involving phoneme correlation, and phoneme recognition results, can effectively detect mispronounced phonemes and missed phonemes, but the detection of inserted phonemes is poor. People's evaluation of pronunciation is intuitive and rapid. However, it is still a difficult problem for computers to synthesize various features and give feedback in line with expert opinions. Given the difficulty of oral English teaching in current English teaching practices, this paper used computer technology, network technology, natural language processing technology, speech processing technology and human-computer interaction technology to propose a spoken language training system based on automatic speech evaluation. The system solves the biggest problem in oral training application from the environment, provides a learning method that can break through time and space constraints, and allows students to learn any time and anywhere. Moreover, it can alleviate the psychological pressure placed on students who are afraid of making mistakes. The research field of computer-aided language learning systems based on speech technology is still in its infancy, and speech recognition is also a fertile research area of speech technology. Moreover, research on automatic speech evaluation based on speech recognition is now in full swing. At present, the application of automatic voice evaluation in oral training systems enables the learner to accurately understand his own speaking ability, locate the pronunciation error, and receive corrective advice. However, the current evaluation results indicate that the positioning and correction of the discourse is not very accurate and far from perfect. Therefore, in future, the project team intends to investigate ways to detect and locate the pronunciation errors more accurately and give correction suggestions.

REFERENCES

1. Basic D., Shanley C., Gonzales R.(2017). The Impact of Being a Migrant from a Non-English-Speaking Country on Healthcare Outcomes in Frail Older Inpatients: An Australian Study, Journal of Cross-Cultural Gerontology, 32(4):447–460.
2. Dorothy N. D., Adrienne R., Neuman A. C. (2017). Speech Recognition in Nonnative versus Native English-Speaking College Students in a Virtual Classroom, Journal of the American Academy of Audiology, 28(5):404–414.
3. Diamantoulakis P., Kapinas V., Karagiannidis G. (2015). Big data analytics for dynamic energy management in smart grids. Big Data Research, 2 (3), pp. 94–101.
4. Ferrer, M.A, Vargas, F., Travieso, C.M. and Alonso, J.B. (2010) 'Signature verification using local directional pattern (LDP)', Proc. – Int. Carnahan Conf. Secur. Technol., pp.336–340.
5. Ferrer, M.A., Alonso, J.B. and Travieso, C.M. (2005) 'Offline geometric parameters for automatic signature verification using fixed-point arithmetic', IEEE Trans. Pattern Anal. Mach. Intell., Vol. 27, No. 6, pp.993–997.
6. Guerbai, Y., Chibani, Y. and Hadjadji, B. (2015) 'The effective use of the one-class SVM classifier for handwritten signature verification based on writer-independent parameters', Pattern Recognition, Vol. 48, No. 1, pp.103–113.
7. Hu, J. and Chen, Y. (2013) 'Offline signature verification using real adaboost classifier combination of pseudo-dynamic features', in 12th International Conference on Document Analysis and Recognition, August 2013, pp.1345–1349.
8. Irfan M., Iqbal J., Iqbal A., Iqbal Z. (2017). Opportunities and challenges in control of smart grids–Pakistani perspective. Renewable & Sustainable Energy Reviews, 71, pp. 652–674
9. Julio A. Why tourism research in non-English speaking systems is ignored. Tourism Recreation Research, 2018, 43(3):400–402.
10. Kabalci Y. (2016). A survey on smart metering and smart grid communication. Renewable & Sustainable Energy Reviews, 57, pp. 302–318.
11. Liu F., Zhou Z. (2015). A new data classification method based on chaotic particle swarm optimization and least square-support vector machine. Chemometrics & Intelligent Laboratory Systems, 147 (15), pp. 147–156.
12. Muslem A., Abbas M. (2017). The Effectiveness of Immersive Multimedia Learning with Peer Support on English Speaking and Reading Aloud, International Journal of Instruction, 10(1):203–218.
13. Miles K. P., Ehri L. C. (2017). Learning to Read Words on Flashcards: Effects of Sentence Contexts and Word Class in Native and Nonnative English-Speaking Kindergartners, Early Childhood Research Quarterly, 41:103–113.
14. Mawson C.(2017). Carnegie Speech Company. NativeAccent. English Speech Training, Journal of Second Language Pronunciation, 3(1):140–143.
15. Niolaki G., Terzopoulos A., Masterson J. (2017). A sublexical training study for spelling in a biliterate Greek- and English-speaking child, Neuro psychological Rehabilitation, 27(4):540–562.
16. Pingkuo L., Zhongfu T. (2016). How to develop distributed generation in China: in the context of the reformation of electric power system. Renewable & Sustainable Energy Reviews, 66, pp. 10–26.
17. Salem A., Shaffer J., Kublik R. (2017). Microstructure-informed cloud computing for inter operability of materials databases and computational models: microtextured regions in Ti alloys. Integrating Materials & Manufacturing Innovation, 6 (1), pp. 111–126.
18. Sun K., Yan D., Hong T. (2014). Stochastic modeling of overtime occupancy and its application in building energy simulation and calibration. Building & Environment, 79 (5), pp. 1–12.
19. Schleich J., Faure C., Klobasa M. (2017). Persistence of the effects of providing feedback alongside smart metering devices on household electricity demand. Energy Policy, 107, pp. 225–233.
20. Zhou L., Wang B., Jiang J. (2017). Predicting the gas-liquid critical temperature of binary mixtures based on the quantitative structure property relationship. Chemometrics & Intelligent Laboratory Systems, 167, pp. 190–195.