# Identification of Alzheimer's Disease Patients Based on Oral Speech Features

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***Abstract*— Screening Alzheimer's disease (AD) patients quickly and non-invasively is of great challenge in the field of clinical medical. In this study, a method based on oral speech features for AD patients identification was proposed. AD (27 people), MCI (Mild Cognitive Impairment, 42 people) and HCs (Healthy Controls, 25 people) were recruited to make a detailed description of the Cookie Theft picture. Linguistic features and acoustic features were extracted manually and automatically respectively from the speech. Based on these features, Support Vector Machine (SVM) classifier was adopted to model and identify AD patients. The results based on linguistic features and acoustic features reached an accuracy of 94.2% and 93.62% respectively. The results suggested that a validated oral task could be further used with automatic algorithm in AD identification. This study is the first study to classify Chinese AD patients with linguistic features and acoustic features, sending important message for rapid AD early screening based on a quick ecological oral task.**

## I. INTRODUCTION

Alzheimer's disease is a comprehensive progressive cognitive disorder. According to World Alzheimer Report 2018[1], there were about 50 million patients in the world, and the global dementia-related expenditure were about 1 trillion US dollars in 2018. With the rapid growth of the elderly population, the number of AD patients will rise to 82 million, and the related expenditure will increase to 2 trillion US dollars by 2030. How to diagnose AD patients quickly is a major challenge for better prevention. The current standard practice is using biomarkers and neuroimaging for diagnosis [2], but this invasive method is expensive, time consuming, and hardly accessing. How to carry out non-invasive rapid screening is the forefront of current research. Before biological pathology progress and significant brain structural impairment, AD patients show a grade loss of memory, understanding, judgment, thinking, language [3], which provides a clue for rapid screening development.

Language competence is unique for AD screening. The hallmark of cognitive impairment such as episodic memory, semantic memory deficit, can be well measured by language tasks [2] [4] [5]. By manually labeling the linguistic features, semantic fluency and picture description tasks have been successfully applied to identify AD [6] [7] [8]. However, there still several problems remain unanswered. First, linguistic features include phonetic semantic, syntactic and textual cohesive features, previous studies have mainly adopted phonetic, semantic, syntactic features in classification [3] [6] [9], but recent studies revealed broken text coherence in AD patients [11] [13]. Moreover, studies found that semantics and syntax have different degradation patterns in the course of AD [3] [12] [13]. It raised an open question that how each level of features contribute to AD identification and whether fused features would improve the identification effect. Second, Chinese differs from Indo-European languages [7] [9], it is critical to establish a valid AD screen model in China with rapidly increased AD patients. Third, although the manual labeling method can make full use of human language experience, it is difficult to apply in large-scale screening. Few studies have shown automatic feature extraction from long audio could be used to distinguish AD from HCs [7], which mimic to long duration of the speech in the linguistic feature extraction. However, the acoustic features related research extracted almost related to silence and transcription [5] [7], whether an algorithm based on short segments with acoustic features irrelevant to transcription hasn't been well addressed.

In allusion to the problems mentioned above, the study mainly covers the following respects. Firstly, we explores the identification effects of different aspects of linguistic features on AD patients alone. Further, the fusion of various linguistic features is carried out to compare with the effect of single features. Since linguistic features rely on artificial and expert knowledge, in order to improve the implementation of AD patients identification, the study models and classifies AD patients by extracting acoustic features of short speech segments automatically. It would provide a clue for the automation of early screening of AD patients.

## II. METHOD

In this study, AD classification was carried out based on oral speech features. The overall framework of the system is shown in Fig. 1. The system includes the training phase and test phase. During the training phase, firstly, the training data are preprocessed by phonetic transcription, segmentation and denoising. Secondly, oral speech features was extracted, which included manually marked linguistic features and automatic acoustic feature extraction. The different level of linguistic features includes phonetic features, semantic features, syntactic features and textual cohesive features. At the same time, we combine the single linguistic features to obtain the fused linguistic feature sets. Acoustic features include I-vector features, pathology-related features and their fusion features. In the end, SVM classification models of different participants (AD, MCI and HCs) were trained respectively.

In the test phase, the test data experienced the step of preprocessing and feature extraction similarly, then the feature sets would be as the input of the trained SVM model. In the end, the classification of the test data is identified through judgment scoring, and the prediction result is obtained.

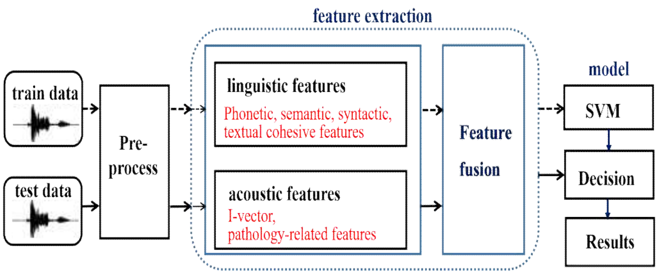


Fig. 1 The framework of the system for identification of AD.

## III. LINGUISTIC FEATURES EXTRACTION

The knowledge about the distinctive linguistic features associated with different neurodegenerative diseases has progressively improved in recent years [10] [11] [13]. To quantitatively and qualitatively describe the language performance, four levels of linguistic features were used in the present study: phonetic, semantic, syntactic and textual cohesive features. The features were widely used in previous studies. As the study is based on Chinese participants, several features were additionally adopted for better representation of Chinese by referring to the work of Zhang et al. [14] and Wu et al. [15].

### *A. Phonetic features*

Phonetic features describe language production at the sound level. In this level, a total of 9 dimensions of phonetic features were included. According to previous research [14] [15], we adopted the false starts [14], the mean length of run, speech rate, articulation rate, silent pauses (rate and duration ratio), filled pauses (rate and duration ratio) [5] [16]. The stronger the ability to control language knowledge, the higher the fluency, that is to say, fluency reflects the ability to control language. The phonetic features here could also as acoustic features in fields of signal processing.

### *B. Semantic features*

Semantic features capture impairments at word and content levels. At the word level, examining part of speech distribution (type-token ratio, noun rate, pronoun rate, pronoun-noun ratio, the number of undefined pronoun) and word fluency (word-finding difficulties, revision, repetitions (including the types and times of repetitions). The quality of the output content examined at content level, including the total number of word information content, information unit, semantic errors, content output before doctor's cue (word count and percentage)[16]. A total of 20 dimensions of semantic features were included.

### *C. Syntactic features*

Syntactic features provide a measure of the syntactic complexity of discourse. The syntactic features we used including well-formed sentences, incomplete sentences, number of quantifiers, verb rate, number of prepositional phrases, number of coordinate phrases, syntactic errors, number of T-units, mean T-unit length, number of clauses of per T-units. Among them, all the indexes of T-unit are adjusted according to the study of Chen [16] aiming at the syntactic features of Chinese. Syntactic features have a total of 13 dimensions.

### *D. Textual cohesive features*

Textual cohesive features examine the cohesion and coherence of the text, includes topic-chains, total number of topic chain clauses, zero NP, conjunction rate [12] [14]. The first three features related to the topic chains were adjusted according to the characteristics of the Chinese language. A total of 4 dimensional features were included.

### *E. Feature Fusion*

The independent features were also fused to form a plurality of fused feature sets, including a set with semantic and syntactic feature fusion (33 dimensions), a set with semantic and phonetic feature fusion (29 dimensions), a set with syntactic and phonetic feature fusion (22 dimensions), a set with syntax and textual cohesive feature fusion (17 dimensions), a set with semantic and textual cohesive feature fusion (24 dimensions), a set with phonetic and textual cohesive feature fusion(13 dimensions), a set with phonetic, syntax and semantic feature fusion (42 dimensions), and a set with all linguistic futures including phonetics, semantics, syntax and textual cohesive feature fusion (46 dimensions).

## IV. ACOUSTIC FEATURE EXTRACTION

Due to the complexity and variability of AD patients' spoken speech, the acoustic features extracted in this paper include: I-vector features and pathology-related features. To further improve the characterization of AD patients' speech generic features, the fusion of I-vector and pathology-related acoustic features was performed to characterize AD patients' generic information.

### A. I-vector feature extraction

The acoustic feature I-vector commonly used for speaker identification and language identification. The I-vector here is used as a discriminative factor feature to distinguish AD patients, MCI patients and normal elderly.

The extraction steps of I-vector are as following. Firstly, Mel Frequency Cepstral Coefficient (MFCC) features of each subject's audio are extracted, and refine the mean super-vector M in GMM (Gaussian Mixture Model) according to Joint Factor Analysis (JFA) theory [16], as shown in Formula (1):

$$M = m + Tw \tag{1}$$

M is a super-vector independent of the specific target group and channel, which is usually replaced by mean super-vector in Universal Back-ground Model (UBM). T is total-variability matrix, which is obtained by Expectation Maximization (EM) algorithm iteration estimation. T matrix estimation process is the key of I-vector extraction. The obtained I-vector feature is a characterization of audio segments. In this paper, Kaldi toolkit is used for extraction of I-vector feature [17].

### B. Pathology-related acoustic features extraction

Speech contains much information about the speaker. Analyzing the audio signal has significance for recognition and interpretation of the distinct information contained. Disease causes changes in audio signals. Acoustic analysis of pathological speech can reveal the information of disease's influence on sound [5] [9]. In this paper, we reviewed the research on pathological voice and selected the relevant features as the pathology-related features here [18] [19]. Pathology-related acoustic features are extracted by toolkit OpenSMILE [20], the features were selected from the AVEC2011 feature set, including energy in bands from 250–650Hz, 1kHz–4kHz; zero-crossing rate (zcr); pitch (F0);harmonic noise ratio (HNR); shimmer; jitter; voicing final unclipped; Combining these statistical features with their functionals formed a 65-dimensional feature set. Pathology-related acoustic features in this paper are extracted.

## V. EXPERIMENT

The experiment in the study includes on two systems: (1) training models and perform classification based on linguistic features; (2) training models and perform classification based on acoustic features.

### A. Data Acquisition

The experiment recruited 27 AD, 42 MCI and 25 HCs, all were over 65 years old at the test time, from the First Affiliated Hospital of Medical School of Zhejiang University. All patients were diagnosed by a consensus panel including three senior neurologists, based on the criteria of the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition [21], see detailed criteria in Zhang et al. [22]. This study received approval from the First Affiliated Hospital of Medical School of Zhejiang University Hospital institutional review board and the methods were carried out in accordance with the Declaration of Helsinki. Informed written consent was obtained from each participant.

We adopted widely used Cookie Theft for picture description [2]. The participants were asked to descript the picture as much and detail as possible, within 2 min. The microphone device was used to record the audio data of the participants during their task, unified the sampling rate, the number of bits to 16 kHz, 16 bit, and finally the database of the study is formed.

### B. Experimental Process

Firstly, voice preprocessing is carried out for the collected database, including denoising, segmentation, labeling, etc. Secondly, feature extraction is carried out, including linguistic features extraction and acoustic feature extraction. Then normalize the extracted feature datasets. We use the Libsvm [23] which is a free, open-source toolkit to model and classify the features. In the classification stage, we searched for the best SVM parameters during training using the standard Libsvm's grid search algorithm using k-fold cross-validation.

The study opted a 5-fold cross-validation: divide the feature set into 5 subsets randomly, each subset as test set once, the rest is employed as training set, cross-validation is repeated 5 times, one subset is selected for testing each time, and the average cross-validation recognition accuracy rate of 5 times is used as the result. So as to verify the validity of selected features and the accuracy of the system.

### C. Linguistic features

In this paper, classification based on linguistic features is mainly divided into two aspects: classification based on single feature and fused feature; these linguistic features derived from manual labelled transcription text. Fig. 2 presents the results of classification based on single features at different levels.

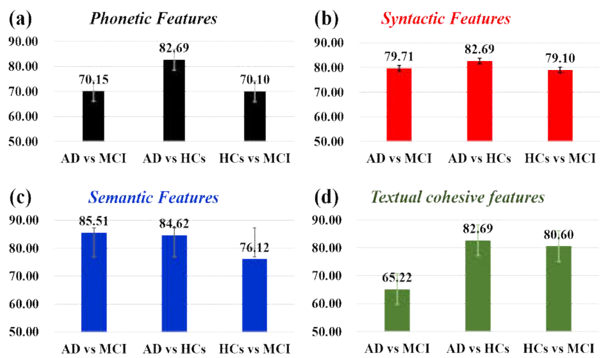


Fig. 2 Classification Results of Individual Linguistic Features (%)

Fig. 2-(a) and Fig. 2-(b) revealed that, the classification effect based on phonetic features and syntactic features in AD-HC is higher than that in MCI-AD and HCs-MCI classification. The classification across groups indicates that the phonetic and syntactic functions have changed to a certain extent when HCs transits to AD. Fig. 2-(c) showed that the

accuracy is relatively low in classification between HCs and MCI, however, that is significantly improved in AD-HCs and AD-MCI classification. The results presented in Fig. 2-(c) indicates that semantic function has changed significantly during the course of MCI to AD. Fig. 2-(d) revealed that classification accuracy based on textual cohesive feature is better for HCs-MCI and HCs-AD, but not MCI-AD. The results from Fig. 2-(d) indicates that textual cohesive features have been impaired in MCI and AD than HCs, so that only the accuracy in MCI-AD classification is low. Taking the results from Fig. 2 together, it clearly showed that language performance damage varied among different aspect linguistic features.

In a second analysis, classification for these fused linguistic features, with results shown in Table 1. The classification accuracy has increased to a certain extent and the best results in group AD-HCs reaches 94.23%, and 91.30% in group AD-MCI.

Table 1: The accuracy of the fused linguistic features (%).

| Features | AD vs MCI | AD vs HCs | HCs vs MCI |
|---|---|---|---|
| Semantic+ Syntactic | 82.61 | 88.46 | 77.61 |
| Phonetic+ Syntactic | 84.62 | 84.62 | 73.13 |
| Phonetic+ Semantic | 89.86 | 92.31 | 74.63 |
| Syntactic + Textual cohesion | 84.06 | 82.69 | 77.61 |
| Semantic+ Textual cohesion | 82.61 | 86.54 | 76.12 |
| Phonetic+ Textual cohesion | 85.51 | 86.54 | 73.13 |
| Phonetic+ Semantic +Syntactic | 91.30 | 94.23 | 71.61 |
| **Linguistic features** | **91.30** | **94.23** | **79.10** |

As shown in Figure 3, the average classification accuracy of fused features is significantly improved compared with the result based on independent features.

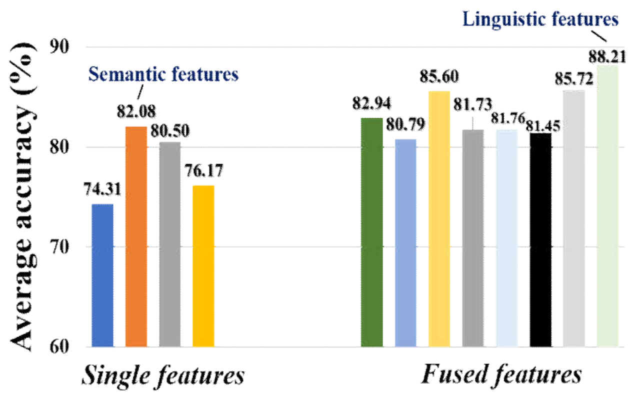


Fig. 3 The average accuracy distribution chart of single feature set and

## D. Acoustic features

In view of the complexity of manual extraction of linguistic features, and also, the language information is not abundant for short speech segments, we induce the acoustic features. The acoustic feature extraction in this study based on the speech segment level, including 1s, 2s, 4s, mainly examining the effect of speech segment length on AD recognition. The number of Gaussian Mixtures is fixed at 128, and the dimension of I-vector is 100. The recognition effect of subjects based on acoustic features with short speech segments is mainly presented in Table 2.

Table 2: The classification results of the acoustic features (%)

| | | I-vector | Pathology-related | I-vector+ Pathology-related |
|---|---|---|---|---|
| 1s | AD vs MCI | 65.86 | 66.58 | 72.58 |
| | AD vs HCs | 68.72 | 77.80 | 78.57 |
| | HCs vs MCI | 62.89 | 63.85 | 66.39 |
| 2s | AD vs MCI | 70.95 | 76.10 | 79.32 |
| | AD vs HCs | 74.06 | 79.98 | 82.33 |
| | HCs vs MCI | 66.89 | 63.98 | 70.17 |
| 4s | AD vs MCI | 75.16 | 78.96 | 80.38 |
| | AD vs HCs | 74.10 | 83.36 | 84.97 |
| | HCs vs MCI | 69.92 | 69.79 | 71.73 |

The above results revealed that the results of AD classification based on pathology-related features are higher than I-vector. At the feature level, compared with that of single acoustic feature, fused features contain more information, and the classification effect is improved.

From the perspective of the segments length, the longer the speech segment length is, the more information it contains, and the better the classification effect is correspondingly.

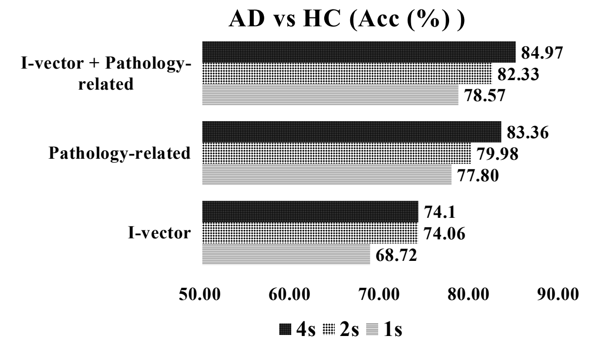


Fig. 4 The classification result of AD-HC based on acoustic features.

Taking the AD-HC group as an example, as shown in Fig. 4.

The results shows that the fused feature of 4s speech segments performed best, and the accuracy reaches 84.97%. Additionally, we added a one vs all classification experiment for 4s speech segments. The results are exhibited in Table 3.

Table 3: One vs all classification based on acoustic features (%)

| features | AD-{HCs, MCI} | HCs-{AD, MCI} |
|---|---|---|
| I-vector | 73.24 | 71.01 |
| Pathology-related | 79.93 | 79.58 |
| I-vector + Pathology-related | **82.16** | **81.1** |

One vs all classification experiment results for acoustic features show that the fused features have distinct classification effect. And the fine classification accuracy reaches 82.16%.

The identification of AD patient based on acoustic features has achieved certain effects and solved the problem of difficult manual extraction of linguistic features to a certain extent. Furthermore, to solve the problem of small datasets in this study, we made some changes and attempts based on 4s speech segments with high performance. The following two steps were carried out: 1. Adjust the parameters of I-vector acoustic features, reduce the number of Gaussian Mixtures and the dimension of I-vector to 64 and 16 respectively; 2. Data augmentation performed by adjusting the audio speed. The audio speed here adopted is 0.9, 1.0 and 1.1, which will triple the original data. Subsequent modeling and classification are the same as before, using SVM classifier with grid search algorithm and 5-fold cross validation. The detailed results are listed in Table 4.

Table 4: Results of dimension adjustment and data amplification for I-vector features of 4s speech segments (%)

| | **AD vs MCI** | **AD vs HCs** | **HCs vs MCI** |
|---|---|---|---|
| 100 dimension | 75.16 | 74.10 | 69.92 |
| 16 dimension | 89.56 | 89.62 | 81.29 |
| **16 dimension (augmentation)** | **90.45** | **93.62** | **88.50** |

The results show that the identification accuracy of the 16-dimensional I-vector is increased by approximately 10 points in relation to 100-dimensional I-vector, and the accuracy in group AD-HC reaches 89.62%. Meanwhile, extracting the 16-dimensional I-vector feature from the voice by data augmentation, the classification effect is also enhanced. Accordingly, the accuracy in group AD-HC is up to 93.62%, which is comparable to the effect of linguistic features.

## VI. Conclusions

In this paper, we proposed an approach based on oral speech features for identification of Chinese AD patients. The high accuracy based on the linguistic features validated the task. The high accuracy based on the acoustic features further suggest that an automatic classification model could be used in Chinese AD identification.

The present study confirmed that linguistic features extracted from speech in descripting the Cookie theft could be used in Chinese AD identification [24]. Moreover, the results clarifies that the deficit varied across different linguistic features. By comparing the individual features, the results revealed that linguistic features damaged differently in AD progression, with text cohesive feature significantly impaired in MCI and AD, while the semantic feature significantly impaired in AD, and phonetic and syntactic features damaged incrementally from HC to MCI and to AD. Critically, compared with the result of independent features, the fused linguistic features effect is significantly improved, reaching a highest accuracy at 94.23%. The overall results also validated the short oral task can be ecologically used in AD identification, by extensively using the linguistic features.

A critical contribution from the present study is that an automatic algorithm has been successfully applied in AD identification. Specifically, the accuracy reached as high as 84.97% in fused acoustic features in between group identification among the three groups, and as 82.16% in one vs all group identification. The results show that the classification effect based on pathological features is better than that of I-vector features, and their fusion features is better than that of single acoustic features. The slightly lower accuracy in the automatic algorithm than the linguistic feature approach may due to two facts. One reason is that, the short audio may not fully capture the pathological deficits in AD progression, which may be better captured by linguistic analysis. The other reason is that, such an automatic algorithm may heavily depend on large sample. The second reason could solved by data augmentation. Nevertheless, the overall accuracy of 93.62% is compatible with previous reports of 86% of accuracy [8]. The present study validated that an automatic algorithm approach based on short speech segments in AD identification, could largely reduce the linguistic feature extraction effort.

We admit that this study is preliminary; particularly, the discriminative features used here are rather vague. A better and more detailed feature selection method may significantly improve the approach, which we leave as the future work. And also we would try to apply deep neural network model for identification of AD patients.

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