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Medical Difficult Airway Detection using Speech Technology

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Abstract

The detection of the difficult airway is an important process in patients undergoing surgery with general anesthesia. The inappropriate management of the difficult airway is associated with morbidity and mortality. However, rational clinical evaluation of the difficult airway have several limitations. In this paper, we explore how to use speech technology to recognize the difficult airway, and we further apply the deep speaker recognition model to the prediction of the difficult airway. Experiments are carried out on a well-designed dataset recorded from 1189 speakers in the hospital. Then, the speaker embedding is taken as the input of the final support vector machine (SVM) to make the decision. Moreover, the performance of the proposed models outperforms traditional clinical examination methods by a large margin.

Index Terms: difficult airway, speaker recognition, support vector machine

1. Introduction

A difficult airway is defined as the clinical situation in which a conventionally trained anesthesiologist experiences difficulty in facemask ventilation, tracheal intubation, or both [1]. Failure to detect the difficult airway is the most important factor contributing to major complications associated with long-term morbidity and accounts for 25% of anesthesia-related deaths [2]. Accurately detecting the potential difficult airway is the key point to decrease the morbidity and mortality caused by failed airway management. However, the existing clinical assessment of the difficult airway is neither convenient nor accurate enough. Then, the extraction of several physical features and the results of the bedside screening tests used in the clinical practice to detect the difficult airway rely on manual measurement and subjective judgement [3]. Recently, advanced imaging techniques such as computer tomography, magnetic resonance imaging and ultrasound treatment have been used to assist airway management. Unfortunately, these procedures are generally expensive, time-consuming, and invasive for patients due to radiation exposure [4].

Nowadays, automatic analysis and assessment of speech and voice have become an important developing direction for diagnosing many diseases. Some attractive results have been contributed in many works. For example, the speech articulatory movements have a considerable impact on the diagnosis of Parkison diseases [5]. Cough sounds can be used to diagnose COVID-19 [6] accurately. Further, obstructive sleep apnea has long been investigated for the severity estimation based on speech signals [7, 8].

Abnormal or particular speech features from speakers with the difficult airway can be expected to result from an altered vocal tract structure or craniofacial abnormalities. Hereafter, the patients' speech or voice should benefit the detection of the difficult airway. Indeed, many works have used the i-vector system [9] coming from the speaker recognition [10] to map an utterance to a single embedding for diagnosing diseases [7]. Also, the deep speaker recognition systems have achieved great success for speaker verification [11, 12].

In this paper, based on our previous work [13], inspired by other works involving disease diagnoses such as obstructive sleep apnea and COVID-19 based on speech features, we apply speech technologies to detect the difficult airway including extracting speaker-related features by the use of the ResNet and the ECAPA-TDNN. The experimental results show a significant promotion in comparison to traditional clinical examination methods for accurately detecting a difficult airway. To the best knowledge, this work is the first to use speech technologies systematically for detecting the difficult airway. The main contents are as follows,

1. The state-of-the-art speaker embeddings are applied to recognize the difficult airway, which outperforms traditional methods in a large margin.
2. Different speech features are explored for detecting the difficult airway.
3. The system using speech technology achieves better accuracy under much more convenient usages.

Also, we introduce the problem formulation and the framework of our proposed difficult airway detection system in Section 2, together with the details of experiments including dataset, implementation in Section 3. The results, analysis, and discussions are presented in Section 4.

2. Methods

2.1. Problem Formulation

A dataset containing recordings from patients with labels indicating whether suffering from the difficult airway. The dataset is expressed as follows:

$$S = \{x_n, y_n\}_{n=1}^{N} \tag{1}$$

where $x_n \in \mathcal{R}^p$ denotes the audio information and $y_n \in \{0, 1\}$ denotes whether the sample has difficult airway.

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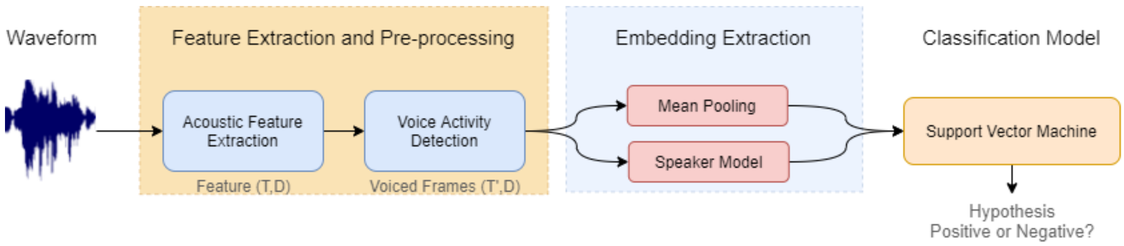

Figure 1: *The framework of the proposed difficult airway detection system*

The goal is to learn a binary classifier $f(\theta)$ for a given unseen recording x_{test} for minimizing the difference between the ground truth label y_{test} and the prediction $\hat{y} = f(\theta, x_{test})$.

2.2. Difficult Airway Detection Using Classification Model

Our pipeline has two branches: raw speech feature based and speaker embedding based. With the inspiration of the work that diagnoses obstructive sleep apnea based on speech features [14], the raw pipeline can utilize speech features directly. Meantime, the speaker embedding based pipeline extracts the speaker embedding for the classifier.

Figure 1 shows the framework of the proposed difficult airway detection system. The acoustic features are extracted from the raw waveform and the signal is transformed from the raw waveform to framed features with shape (T, D). Then a voice activity detection system is used to select voiced frames (T', D). After that, the embedding extraction is divided into two cases: with mean pooling and with the speaker model. Finally, the embedding is fed into the classification model.

In detail, in the case of mean pooling for embedding extraction, the voice features are averaged on the time axis to get the embedding. Such a traditional signal processing-based approach is computationally efficient and easy to verify. Also, in the case of the speaker model, the basic acoustic features and voice frames are extracted at first, followed by a speaker model trained on a large speaker recognition dataset. The input of the classification model is the speaker embedding from the speaker model. Here, we adopt classical i-vector speaker embedding and deep learning based speaker embedding.

Subsequently, we use the support vector machine (SVM) to make the final classification. For each utterance, the input of the classification model is a kind of embedding. The model is then trained to predict whether the embedding is positive or negative for the difficult airway decisively. The input variable is firstly mapped to a high dimensional feature space by using a non-linear mapping according to the kernel function in the SVM. After that, the kernel generates features through the similarity measure between points in the original feature space. Finally, a hyperplane is estimated to separate feature space by the label.

2.3. I-vector Speaker Embedding System

The detection of the difficult airway can also be interpreted as identifying the patients from people. So the speaker recognition technologies are used for this task. Actually, i-vector [9] has been used to represent a sequence of acoustic features as a fixed-length vector and adopted in some works for disease diagnosis [5, 7] as well. In order to extract the i-vector, a K-component Gaussian Mixture Model (GMM), denoted as Universal Background Model (UBM), is initially estimated to model common knowledge of the whole data space. Hereafter, a super-vector

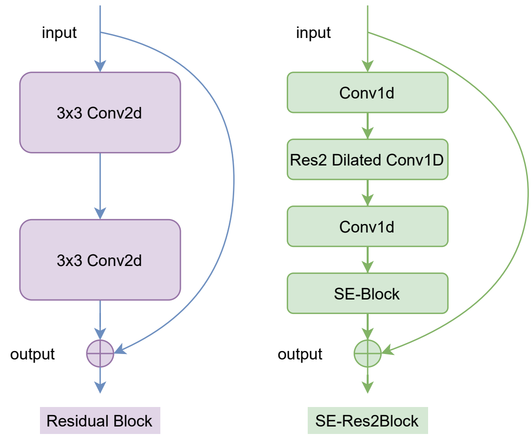

Figure 2: *The basic blocks of deep speaker models: Residual block for ResNet and SE-Res2Block for ECAPA-TDNN*

is constructed by aggregating means of new GMM components adapted from the GMM-UBM. Due to the presence of the unsupervised modeling of GMM-UBM, the existing large-scale data are applied to build the model. The super-vectors are assumed to obey the factor analysis model of the following form:

$$s = m + Tw \tag{2}$$

where s comes from the super-vector of the utterance, m comes from the super-vector of the GMM-UBM, T is the transformation matrix estimated from the training data, and w is the i-vector which represents the speaker information.

2.4. Deep Speaker Embedding System

Deep learning techniques are vastly more effective for many tasks. With enough data, the features can be better modeled using deep neural networks. With the development of the speaker verification task and the inspiration from the framework of x-vector [15], ECAPA-TDNN [12] achieves the state-of-the-art performance on Voxceleb [16] benchmark. Also, ResNet [17] is an important work for speaker verification.

Figure 2 shows the basic blocks of the ResNet and ECAPA-TDNN. ResNet uses 2-dimensional features as input and processes them using 2-dimensional convolution neural network (CNN) layers. The mean and the standard deviation are used to gather frame-level information. Then they are concatenated together and propagated through the embedding layer. Meanwhile, the ECAPA-TDNN utilizes 1-dimensional Res2Net modules with impactful skip connections. Then the "squeeze-and-excitation block" (SE-block) explicitly models channel interdependencies. Finally, the "channel-dependent frame attentive pooling" and the hierarchical features are adopted to leverage the global properties of the recordings.

The deep speaker models are trained to identify the speaker in the training set. In the end, the embedding before the softmax layer is used as the speaker embedding.

3. Experimental Setup

3.1. Dataset

3.1.1. Recording

From December 28 in 2020 to September 16 in 2021, 1189 Mandarin native speakers hospitalized in Shanghai 9th People's Hospital who needed anesthesia were included in this study. Exclusion criteria included subjects with recent upper respiratory tract infection, sinusitis, vocal cord disease, craniofacial surgery, a history of speech disorder, and a history of mental illness. They were asked to read ten sentences under quiet surroundings. The 16-bit hand-held recorders with a sampling frequency of 44.1kHz were used to record speech from participants. The selection of ten sentences is based on the coverage of atonal pinyin. To evaluate the performance of our methods, 201 speakers, including 107 positive samples and 94 negative samples, are left out for the test set. Then we conduct ten-fold cross-validation on the training set. The Cormack-Lehane (CL) grading scale describes how visible the vocal cords are during laryngoscopy, ranging from 1 (full view of vocal cords) to 4 (unseen the epiglottis) [18]. Meanwhile, we use direct laryngoscopy to obtain CL scores for all participants. Based on the CL score, we label patients as ones with difficult airway (CL 3-4) and without non-difficult airway (CL 1-2).

3.1.2. Alignment & Segmentation

The Kaldi [19] chain model trained from AISHELL-2 [20] is adopted to align our data collected from participants. The long recordings are segmented by an energy-based voice activity detection system. Then hypotheses and conversational time marked outputs are generated by the chain model, and the resulting hypotheses are compared with the reference texts. In addition, we adopt the reference text with the lowest edit distance as the final transcript of the segment.

3.1.3. Speaker Verification Dataset

For our speaker system, we use audio data from VoxCeleb 2 dataset [16], which is collected from interview videos uploaded to YouTube. For training, we use the DEV part of the VoxCeleb 2 dataset containing 5,994 speakers and 1,092,009 utterances. All of the audio recordings and speaker identities are from celebrities. Most of the recording scenarios are in a relatively quiet space.

3.2. Support Vector Machine

Using labels based on the CL score, a support vector machine (SVM) is trained to classify the speech features. To evaluate the generalization performance of our algorithm, we employ ten-fold cross-validation for hyper-parameter selection. Then we re-train the model on the whole training set of 988 speakers with the best hyper-parameters according to the ten-fold cross-validation.

For hyper-parameter tuning, the candidate kernels are sigmoid, rational basis function (RBF), linear, and polynomial. And we grid-search the regularization parameter $C \in \{1, 10, 100, 1000\}$ and kernel coefficient $\gamma \in \{0.01, 0.001, 0.0001\}$.

3.3. Raw Speech Features

The audios are down-sampled from 44.1kHz to 16.0kHz. They are framed, lasting 25ms for every 10ms with a 15ms overlap between frames. Then a hamming window is conducted on each frame, and the Kaldi energy-based VAD is leveraged to select voicing frames. After that, we adopt various audio features for each frame, including Mel frequency cepstrum coefficients (MFCC), filter banks (Fbank), linear prediction coefficients (LPC), and formants. All the dimensions of the features except the formants above are set to 40. The formants 1 to 4 are extracted using the praat [21] software. The speech features are then averaged over frames and used as the final feature vector.

3.4. I-vector

The i-vector speaker system is trained following the Kaldi VoxCeleb recipe. The MFCC feature is extracted from the VoxCeleb 2 dataset. Then the universal background model is trained using 2,048 gaussian components. Afterward, the longest 1,000,000 utterances are selected to train the i-vector extractor because short utterances are harmful to the extractor.

3.5. Deep Speaker Models

We train the ResNet34 and the ECAPA-TDNN Large on the VoxCeleb 2 dataset. The 40-dimensional Fbank with a 25ms window size and 10ms shift is used as input, being the same as the setup in the raw speech pipeline. During the training process, audios are randomly chunked to 300 frames. More details about training can be found in literature [17, 12]. For evaluation, the outputs of the last layer of ResNet34 and ECAPA-TDNN are used as the speaker embeddings.

4. Experimental Results

The Aera Under Receiver Operating Characteristic (ROC) curve (AUC) is used for evaluation of the different features and the embeddings. The highest point of the Youden index [22] was designated as the threshold to get the accuracy, specificity, and recall (a.k.a sensitivity). The specificity means the true negative rate in all negative samples, while recall means the true positive rate in all positive samples. The posteriors of samples are averaged through speakers for testing. Then the experiments were repeated ten times, and we reported the average results of AUC, accuracy, specificity, and recall.

4.1. Raw Speech Feature Based Systems

Table 1: *Results of different speech features for difficult airway detection*

Feature	AUC	Accuracy	Specificity	Recall
LPC	0.542	39.0	26.3	83.3
MFCC	0.600	62.6	66.2	50.0
Fbank	0.605	**75.9**	**88.7**	31.0
Formant	**0.709**	71.4	63.0	**86.7**

Table 1 shows the results of the raw speech feature based pipeline. The speech features are extracted from the raw waveform, and they are averaged through the time axis to a single embedding for each utterance. It is observed that for traditional

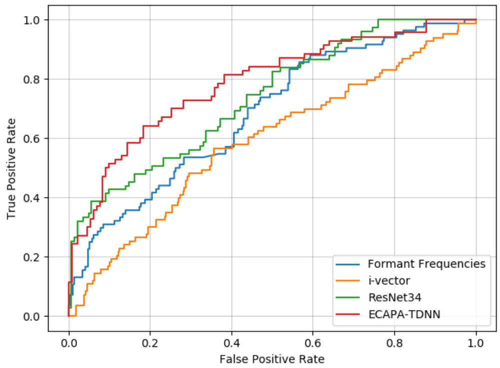

Figure 3: *ROC Curves of the proposed systems*

spectrum-based features, LPC, MFCC and Fbank perform unsatisfactorily from the perspective of AUC. In fact, much information is lost by averaging through features on time directly. These speech features are based on a mathematical transformation of the original audio signals, so the process of extracting features does not exploit the knowledge from data well. However, formant frequencies achieve much better performance than those spectrum-based features. Formant frequencies describe the resonance of the vocal tract and are associated with the internal structures of the upper airway, including its compliance, shape, and dimensions [23]. Although the performance of formant frequencies is not good enough, it still guides us to find ways to characterize the relevant features of the speakers.

4.2. Speaker Embedding Based Systems

Table 2 and Figure 3 show the results of different speaker embedding systems for the difficult airway detection. We adopt two different deep speaker models: ResNet34 and ECAPA-TDNN Large. It is easy to find that the performance of deep speaker embeddings is significantly better than that of the i-vector. This is probably because the i-vector can not model the differences of non-speaker backgrounds (e.g., noise and recording channels) very well in the presence of a large amount of data.

Subsequently, the performance of the deep speaker systems outperforms that of formant frequencies. This states that the ability of deep speaker embeddings is better than that of formant frequencies in characterizing vocal features such as the speaker's structure of the upper airway. The knowledge learned from the large-scale data in deep speaker systems plays an important role in improving performance. Moreover, the results of ECAPA-TDNN are better than that of ResNet-34 in AUC, accuracy and recall except specificity, suggesting that the threshold designated by the Youden Index of ResNet-34 is over-biased towards specificity.

Table 2: *Results of different speaker embeddings for difficult airway detection*

Feature	AUC	Accuracy	Specificity	Recall
Formant	0.709	71.4	63.0	**86.7**
i-vector	0.589	59.6	58.7	62.7
ResNet34	0.737	75.1	**94.4**	38.7
ECAPA	**0.786**	**75.6**	81.7	64.3

4.3. Comparison with Traditional Clinical Examination Methods

Table 3: *Comparison for results from the proposed methods and the traditional clinical methods on difficult airway detection*

Feature	AUC	Accuracy	Specificity	Recall
MMT [24]	0.634	64,7	69.3	51.7
ULBT [25]	0.691	68.3	69.1	66.1
TMD [26]	0.741	69.3	66.9	76.3
Formant	0.709	71.4	63.0	**86.7**
ECAPA	0.786	75.6	**81.7**	64.3
ECAPA + ResNet34	0.789	75.1	79.4	67.1
ECAPA + Formant	**0.807**	**76.6**	74.0	74.3

The modified Mallampati test (MMT), the upper lip bite test (ULBT), and the thyromental distance (TMD) are three traditional clinical examination methods for difficult airway detection. MMT assesses the visibility of the oropharyngeal structures. For ULBT, the range of mandibular movement is assessed by asking patients to bite their upper lip with their lower incisors. TMD refers to a distance between the uppermost border of the thyroid cartilage and the mentum, and is measured with the neck extended and the mouth closed. The MMT, ULBT, and TMD require the patient to be at present and a doctor to perform the test with specialized instruments.

Table 3 shows the comparison results of all traditional clinical methods and the proposed methods. The last two lines are fusion results. The posterior probabilities are averaged over different models for fusion. The fusion of similar systems (ECAPA and ResNet34) has limited improvements over ECAPA. In contrast, the formant frequency system and deep speaker system are complementary to each other. Furthermore, the final speech technology based system outperforms all traditional methods in a large margin in all cases except recall, clearly exhibiting the performance advantages of speech technologies over traditional methods.

5. Conclusions

In this paper, we describe a novel strategy for detecting the difficult airway in human vocal cords based on speech technology. The proposed methods solve problems of being cumbersome, professionally desirable, and insufficiently accurate in traditional methods. Also, the proposed speaker embedding based method shows the ability to identify the difficult airway. Speaker embeddings well characterize the physical structure of the airway. More importantly, due to the ease of speech signal transmission, patients can perform the test simply by using edge devices, being greatly convenient for users. Furthermore, not only does this shed a lot of light on the medical community, but we should also recognize that the application of speaker recognition models goes far beyond speech-related tasks such as verification and diarization. Soon, it is believable that our work will be used in practical clinical applications.

6. Acknowledgements

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