A STUDY ON AUTOMATIC DIAGNOSIS OF MUSCLE TENSION DYSPHONIA BASED ON sEMG

FANG Qiang

Abstract Muscle tension dysphonia (MTD) is a kind of phonation disorder, in which no obvious organic problem can be observed under laryngoscopy. In literature, researchers have investigated the acoustic, electromyographic, and breathy characteristics from a statistic point of view. In this study, we explore the possibility of diagnosing MTD based on task-related surface electromyography (sEMG) signals. In this study, the sEMG signals are collected and transformed to corresponding time and frequency domain features. Then, Flsher' s F-ratio is adopted to select task-related features for automatic diagnosis. Four traditional classification methods(K-nearest neighbor, Classification and Regression Tree, Support Vector Machine, and Logistic regression) are implemented to discriminate MTD patients from healthy people. It is found that the precision can be as high as 80% if proper task and classification method are chosen.
Keywords sEMG, F-ratio, MTD, KNN, CART, SVM, Logistic regression

基于表面肌电的肌肉紧张型发声障碍自动诊断研究

方　强

摘　要　肌肉紧张型发声障碍（MTD）是一种常见的发声障碍。这种类型的发声障碍在歌唱演员、教师及精神焦虑的人群中比较多见。这类患者的声带一般没有明显的器质性病变，但发声时喉部肌肉紧张。临床实践中，医生主要通过问诊、内窥镜检查、嗓音粗糙度评分、触诊等手段对患者的嗓音情况进行评估。可以看出，以上常规手段的诊断结果大多基于医生的主观判断，缺乏客观、定量的判断依据，严重依赖于医生的个人经验。因此，寻找客观、定量的参数，辅助 MTD 的诊断，减少 MTD 的误诊和漏诊，变得十分必要。

前人的研究比较过 MTD 患者和正常人发声过程中声学、肌电及呼吸特征的差异。本研究我们主要考察运用表面肌电信号对 MTD 进行自动诊断的可能性。因此，我们回顾了前人在 MTD 患者肌电信号方面的工作。一部分学者的研究认为 MTD 患者的肌电活动水平与正常人的肌电活动水平有显著差异［6，14］；一部分学者的研究认为 MTD 患者的肌电活动水平与正常人的肌电活动水平没有显著差异［7，17］；还有部分学者发现 MTD 患者不同肌肉肌电信号的相干性与正常人之间有显著差异。我们可以看出，前人的研究并没有取得一致的结果。造成这一现状的原因可能有如下几点：（1）大部分研究调查的人数较少（一般不多于 20 个实验被试），导致结果不稳定；（2）大部分研究只考察了肌电活动水平这一单独参数，可能 MTD 患者与正常人肌电特征存在差异，但差异并不是在肌电活动水平这一特征维度上；（3）考察的任务比较单一，MTD 患者与正常人肌电特征的差异在前人考察的任务中不明显或不稳定。

针对以上问题，在本研究中，我们收集了 47 名 MTD 患者和 22 名正常人在 14 个不同任务（8 个言语任务和 6 个非言语任务），舌骨上肌群、舌骨下肌群、环甲肌、胸锁乳突肌和斜方肌等 5 个肌群左右两侧部分的肌电信号。我们对肌电信号进行降噪和特征抽取等处理，得到 850 维的肌电特征向量。然后，我们用费舍尔 F 比值（Fisher' s F-ratio）这个指标对特征维度进行筛选，对每类任务挑选出前 10 个 F-ratio 值最大的特征维度。最后，基于挑选出来的特征，我们分别采用了 K 近邻（K – nearest neighbor）、支持向量机（SVM）、分类与回归树（Classification and Refression Tree）以及逻辑回归（Logistic

regression）四种方法对数据进行分类实验。结果表明，如果恰当地选择任务和分类方法，分类的正确率能够达到 80% 以上。
关键词　表面肌电，F 比值，肌肉紧张型发声障碍，K 近邻，分类回归树，支持向量机，逻辑回归

1. INTRODUCTION

Muscle tension dysphonia (MTD) is a kind of phonation disorder, in which no evident organic problem can be observed under laryngoscopy. It is originally coined by Morrison [11] and describes adysphonia caused by increased muscle tension of laryngeal and paralaryngeal muscles. And it has been known by other names including muscle misuse dysphonia, hyperfunctional dysphonia, and hyperkinetic dysphonia among others. It is more commonly diagnosed in women, the middle-aged, and individuals who have high levels of stress. It is also more often seen in those who use their voice often such as singers and teachers.

The symptoms for MTD vary from person to person. Hoarseness, pitch range restriction, difficulty of producing voice are typical symptoms associated with MTD. And these symptoms can be caused by a large variety of factors (such as emotional distress, drinking cold water, yelling and shouting, smoking).

MTD presumably is characterized by excessive muscular contraction, and vocal symptoms are combined with excessive glottic and/or supraglottic muscle tension. This suggests that there may exist cues in the activities of related muscles, the behavior of structures in larynx, and acoustic and aerodynamic consequences that help the differentiating of MTD patients from the healthy ones.

In clinical practice, several procedures are commonly used, such as clinical history, endoscopic assessment, harshness rating/perceptual assessment, and palpation rating. Despite the widespread use of the MTD designation, diagnosis and assessment in current clinical practice depends upon subjective interpretation of patient history and physical examination, and heavily influenced by the experience of the clinic practitioners. Hence, it is necessary to develop some objective measure for the detection of MTD.

In literature, several studies had been conducted to investigate whether muscle activity of the MTD patient were significantly different from that of the healthy control, where the sEMG was used to detect the muscle activity. Redenbaug and Reich [14] studied sEMG levels of infrahyoid muscles in normal and vocally MTD speakers. They found EMG levels were significantly larger for MTD speakers. Hocevar-Boltezar et al. [6] investigated the EMG feature in the perioral area and anterior neck before and during phonation. Their results showed a 6 – 8-fold increase of EMG activity. Stepp et al. [16] measured sEMG to explore the intermuscular coherence in the beta band as a possible indicator of MTD. They found the mean coherence in the beta band was significantly lower in MTD group than that in control group. However, there are some experiments that do not support assessing MTD with EMG features. Stepp et al. [17] investigated the sensitivity of the anterior neck sEMG to changes in MTD associated with injection laryngoplasty. They found the perceptual ratings of strain and false vocal fold (FVF) compression were both significantly reduced while sEMG was not significantly reduced. Van Houtte et al. [7] did not detect the increase of sEMG level in patients with MTD and questioned the use of sEMG as a diagnostic tool for distinguishing patients with and without MTD.

Although the above-mentioned studies did not come to an agreement, we can not conclude that sEMG is not appropriate for diagnosing MTD. It is not negligible that, most of the previous studies only explored few sEMG features (Root-Mean-Square, and coherence in beta band). None of them extensively investigated sEMG features of related muscles on vocal tasks. In addition, most of them only investigated on vocal task.

In this study, we attempt to figure out whether we can differentiate the MTD patients from the healthy people by using the activities of muscles in neck area measured by sEMG. To this end, we will collect the sEMG signals of related muscles in a few vocal/non-vocal conditions, extract extensive sEMG features, and conduct classification experiments based on the extracted sEMG features.

2. DATASET

2.1 Subject information

47 MTD patients and a group of 22 normal controls are enrolled in our experiment. The 47 patients with MTD are admitted to Beijing Tongren Hospital affiliated to Capital Medical University from June 2018 to January 2020, aged from 18 to 80 (mean = 38, std = 17.6). Among these patients, 14 of them are males and the other 33 of them are females. In the normal control group, there are 22 cases, aged from 22 to 67 (mean = 33.87, std = 11.97). Twelve of them are males, and 10 of them are females. None of the subjects has supraglottal infection, mental issue, nor muscle tension disorder caused by throat surgery or lesion. All the subjects are evaluated by subjective auditory-perceptual assessment of the voice, the Voice Handicap Index (VHI), acoustic analysis, and psychological scales assessment.

2.2 Data collection

A multi-channel physiological recorder (Australia COMPUMEDICS Grael 48 channels) is used to record the sEMG, ElectroCardioGram (ECG), nasal airflow, and breathing signals (the change of perimeter of the chest and abdomen) synchronously. The audio signal of vocal sound is recorded by a separate audio channel. In the experiment, sEMG electrodes are attached to the left and right parts of trapezius (TRA), SternoCleidomastoid muscles (SC), SupraHyoid muscles (SH), InfraHyoid muscles (IH) and CricoThyroid muscle (CT), as shown in Fig 1.

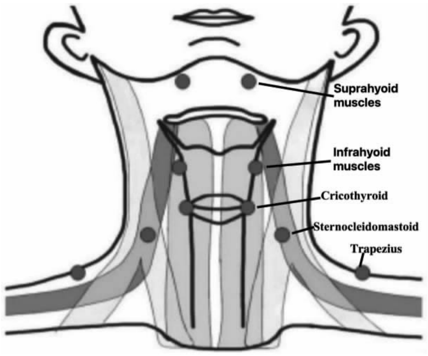

Figure 1 Locations of electrodes of surface EMG

It is hypothesized that the related muscles may be activated abnormally in both vocal and non-vocal tasks for MTD patients. For this reason, the subjects are required to conduct both vocal and non-vocal tasks so as to collect task-related sEMG signals. These tasks recruited in the current study are as follows: turning head left (THL), turning head right (THR), shoulder shrugging(SS), throat cleaning (TC), swallowing (SW), deep breathing (DB), producing prolonged vowel /i/ (PI), high-pitch /i/ (HI), loud /i/ (LI), loud and high-pitch /i/(LHI), prolonged vowel /a/ (PA), high-pitch /a/ (HA), loud /a/ (LA), loud and high-pitch /i/ (LHA), short utterance (SU) (我去黑龙江, 他去无锡市. "I am going to Heilongjiang, he is going to Wuxi City" in Mandarin), loud short utterance (LSU). Between two tasks, subjects are required to take a 10-second break to avoid fatigue.

In this study, the data in task SU and LSU are not used because the data in these

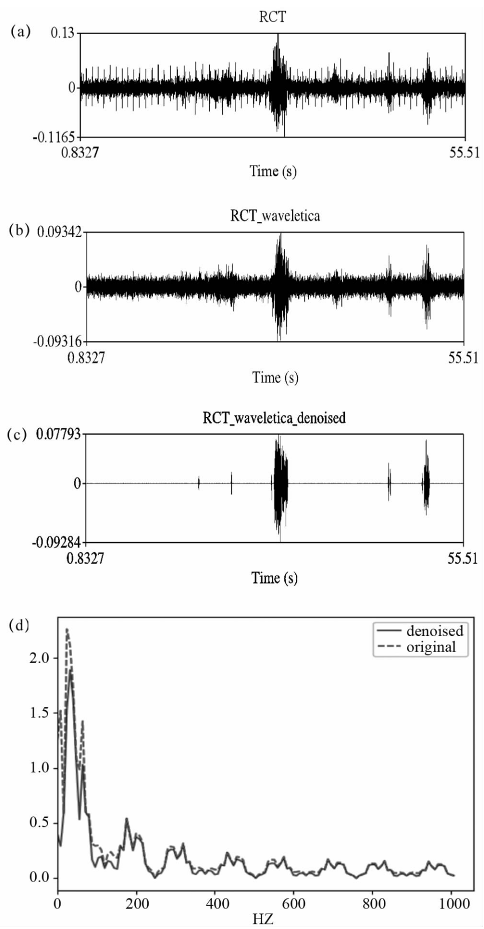

Figure 2　Examples of the original and processed EMG signal. (a) Original signal. (b) Original with ECG-like artifacts removed. (c) Original with both ECG-like artifacts and background noise removed. (d) Spectrum of original sEMG signal (dashed red) and denoised sEMG signal (solid blue).

two tasks are designed to monitor temporal variation of muscle activation and the control of respiration that are not considered in the current study.

2.3　Noise reduction

Usually, there are artifacts and background noise in the collected sEMG signal. Figure 2 (a) gives an example of recorded EMG signal, where the EMG signal sequence is contaminated by some periodic spikes, called ECG-like artifacts, and evident background noise.

The ECG-like artifacts appear when the EMG electrode is placed close to an artery. The ECG-like artifacts will change the temporal and frequency characteristics of sEMG signal. Therefore, the ECG-like artifacts should be removed before feeding sEMG signal to subsequent processing procedure.

In this study, the wavelet-ICA [1] method is implemented to suppress the ECG-like signals. To this end, firstly, a mono-channel signal sequence is transformed to a multi-channel signal sequence by wavelet analysis. Then, the multi-channel signal sequence is decomposed into several independent channels by using Independent Component Analysis (ICA) method. After that, the signals in the channel that has the same periodicity of ECG-like artifacts are removed. At last, the final signal is synthesized by reversing the aforementioned process.

As for the background noise, it is mainly introduced by the data collecting instrument and is assumed stationary. To suppress the background noise, the spectrum subtraction method [2] is applied, where the initial noise spectrum is estimated from the silence portion at the beginning of the signal sequence and updated by using the signals in silent regions dynamically.

Figure 2(b) gives an example of EMG signal of RCT (cricothyroid muscle on the right side) after removing the ECG-like artifacts. Figure 2(c) gives an example of EMG signal of RCT by removing both ECG-like artifacts and background noise. It indicates that the ECG-like artifacts and background noise in the original EMG signals can be effectively suppressed with the proposed noise reduction procedure. Figure 2(d) demonstrates an example of the spectrum of original sEMG signal (dashed red curve) and denoised sEMG signal (solid blue curve). One can see that generally the spectrum of denoised sEMG signal is close to that of the original sEMG, except that some detail frequency components are somewhat different. This indicates that the denoised sEMG signal preserves the nature of the original sEMG signal.

3. FEATURES

Traditional studies on sEMG for MTD patients are mainly based on the sEMG level [6, 7, 14]. In this study, we will extensively explore various features and evaluate their contribution to differentiate MTD patients from normal control.

Generally, features for analyzing sEMG signals can be divided into three groups: time domain, frequency domain, and time-frequency or time-scale representation. In this study, only the time and frequency domain features are considered.

Time domain features are based on sEMG time series. In this study, extensive time-domain features are adopted. They are, Duration from rest to Maximum Amplitude (D2MA), Maximum Phonation Time (MPT), Maximum AMplitude (MAM), the Duration to achieve Maximum AMplitude (DMAM), Integrated EMG, Mean Absolute Value (MAV) [19], Modified mean Absolute Value type-1 (MAV1) [12], Modified mean Absolute Value type-2 (MAV2) [12], Simple Square Integral (SSI) [4], VARiance of EMG (VAR) [13], the third, fourth, and fifth Temporal Moments (TM3, TM4, and TM5) [15], Root Mean Square (RMS) [3], the V-order (V) [18], LOG detector (LOG) feature[18], Waveform Length (WL) [12], Average Amplitude Change (AAC) [5], Difference Absolute Standard Deviation Value (DASDV) [9], Zero Crossing (ZC) [8], Myopulse Percentage Rate (MPR) [5], Wilson AMPlitude (WAMP) [19], Slope Sign Change (SSC) [8], Mean Absolute Value Slope (MAVS) [10], Multiple Hamming Windows (MHW) Histogram of EMG (HIST) [3], Auto-Regressive (AR) [3], and Cepstral Coefficient (CC) [18].

Frequency-domain features are mostly used to study fatigue of muscle and analyze motor unit recruitment. The frequency-domain features used in this study are MeaN Frequency (MNF) [4], MeDian Frequency (MDF) [12] PeaK Frequency (PKF) [3], MeaN Power (MNP) [3], and ToTal Power (TTP) [3], the 1st, 2nd, and 3rd Spectral Moments (SM1 – SM3) [4], Frequency Ratio (FR) [4], Power Spectrum Ratio (PSR) [20], Variance of Central Frequency (VCF) [4].

For the MTD patient, the asymmetry activation of muscles may occur in vocal and non-vocal tasks. This indicates that the asymmetry of corresponding features are possible indicators for diagnosing MTD. Therefore, the difference of the features between the left and right counterparts of the same muscle are calculated as additional features. Moreover, the difference of the instants when activation occurs and disappears between the left and right counterparts of each muscle is adopted to account for the temporal asymmetry. In total, there are 850 features for each vocal/non-vocal task.

4. FEATURE SELECTION

As mentioned in the previous section, there are 850 candidate features and 69 (47 +22) data samples for each task. The number of data sample is much smaller than the dimensionality of extracted feature. In order to avoid the dimension curse, it is necessary to reduce the dimensionality of features by using feature selection techniques. To this end, firstly, the original data are separated into several subsets according to their tasks (shown in section 2. 1). Hence, we obtain 14 subsets in total. Then, for each subse the Fisher' s F-ratio measure is implemented to quantify the contribution of each feature dimension. Lastly, the features whose corresponding F-ratios are larger than a predefined threshold are selected. The F-ratio of the kth feature can be calculated according to Eq. 1.

$$F_{ratio}^{k} = \frac{\frac{1}{M}\sum_{i=1}^{M}(\mu_i^k - \mu^k)}{\frac{1}{\sum_{i=1}^{M} N_i}\sum_{i=1}^{M}\sum_{j=1}^{N_i}(x_i^{k,j} - \mu_i^k)^2} \quad (1)$$

where μ_i^k is the mean of the kth feature in the ith category, μ^k is the mean of the kth feature of data samples in the whole data set, $x_i^{k,j}$ is the value of the kth feature of the jth data sample in the ith category, M is the number of categories (in this study M = 2,), N_i is the number of samples in the ith category.

The denominator is a measure of within-category data dispersion, while the numerator is a measure of between-category data dispersion. Therefore, the larger the F-ratio is, the larger contribution the feature makes in discriminating MTD from healthy controls .

For each subset, the Fisher' s F-ratios of all the feature dimensions are calculated and sorted in descending orders.

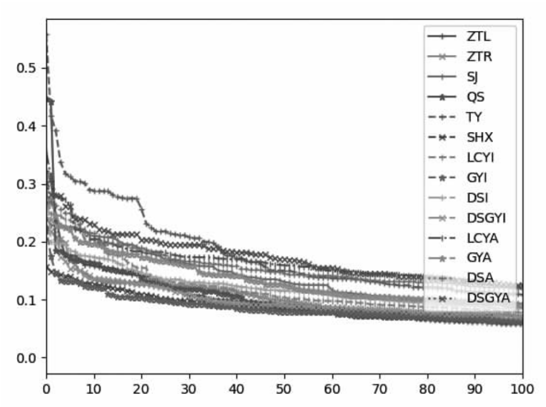

Figure 3 Sorted F-ratios for each non-vocal and vocal task

As shown in Figure 3, the Fisher' s F-ratio decreases dramatically at first, then arrives at a relative stable region. Here, we determine a predefined threshold with the elbow criterion. In this study, for each task, the feature dimensions with the first 10 highest F-ratios are selected as the inputs to classifiers. The details are shown in Table 1.

If we take a look at the details in Table 1, we can notice that the feature RMS (used to measure muscle activation level) is not one of the selected 10 features with the highest contribution to discriminating the MTD patients from the controls in most vocal and non-vocal tasks. In addition, even for similar vocal task, for example producing vowel /i/, the features that make the highest contribution to differentiating MTD patients and controls differs a lot. This may be the reason why the previous studies did not come to a consistent conclusion.

Table 1 The 10 features selected based on F-ratio for each task

Task	Muscle & feature
THL	LIH: AR_ 4 RSH: MNP, SSI, FR_ diff SC: AR_ diff_ 1, CC_ diff_ 0, CC_ diff_ 1, CC_ diff_ 2, CC_ diff_ 3, VCF_ diff
THR	SC: HIST_ diff_ 4, HIST_ diff_ 7, LSC: PKF RSC: ZC TRA: AR_ diff_ 4, CC_ diff_ 3, MDF_ diff, PKF_ diff LTRA: CC_ 3, ZC
SS	CT: MHW_ diff_ 0, MHW_ diff_ 1, MHW_ diff_ 2 IH: AAC_ diff, DASD_ diff, RMS_ diff, V_ diff, WL_ diff, SC: DASD_ diff, AR_ diff_ 2
TC	CT: MPR_ diff RCT: MPR, ZC, SC: PSR_ diff LSC: PSR LSH: DASD, MAV_ 1, RMS, V RIH: PKF

续表

Task	Muscle & feature
SW	LIH: LOG RIH: LOG LSH: LOG, MAV_ 0, MPR RSH: AAC, HIST_ 0, LOG, MPR LTRA: ZC
DB	CT: SSC_ diff, RCT: VCF TRA: AR_ diff_ 2 LTRA: CC_ 3 SC: MAV_ 2_ diff, MAVS_ diff_ 1 RSC: HIST_ 0, HIST_ 5, HIST_ 6, HIST_ 8,
PI	CT: FR_ diff SC: FR_ diff, CC_ diff_ 2 LSC: SSC RSC: DUR, AR_ 1, CC_ 0, SSC, VCF, WAMP TRA: CC_ diff_ 2
HI	CT: DUR_ diff LCT: AR_ 3 IH: MNP_ diff, SM_ 1_ diff, SSI_ diff, TTP _ diff SC: DUR_ diff TRA: AR_ diff_ 3 LTRA: AR_ 3, MAV_ 2
LI	LSH: WL, HIST_ 0, HIST_ 1, HIST_ 2, HIST_ 3, HIST_ 4, HIST_ 5, HIST_ 8 RSH: HIST_ 6 SC: PSR_ diff
HLI	IH: LOG_ diff, CC_ diff_ 2, MPR_ diff LSC: HIST_ 1, HIST_ 2, HIST_ 8 RSC: HIST_ 1, HIST_ 2, HIST_ 5, HIST_ 6
PA	LIH: DUR, SSC, WAMP RIH: DUR, SSC, WAMP LSH: HIST_ 1, HIST_ 2, HIST_ 3, HIST_ 4
HA	SC: PSR_ diff LSC: AR_ 1, AR_ 2, CC_ 0, RSC: AR_ 2, AR_ 4 TRA: AR_ diff_ 1, MDF_ diff, CC_ diff_ 0, CC_ diff_ 2, CC_ diff_ 3

续表

Task	Muscle & feature
LA	CT: MPR_ diff, LSC: DASD, HIST_ 0, INTE, AR_ 2, RMS, V, RSC: DASD, RMS, V
HLA	IH: FR_ diff RIH: SSC LSH: DASD, RMS, V RSC: DASD, INTE, RMS, V, WL

5. EXPERIMENT

5.1 Settings

Four classical classifiers are implemented to explore the possibility of discriminating MTD with EMG features. They are K-nearest neighbor (KNN), Classification and Regression Tree (CART), Support Vector Machine (SVM), and Logistic regression.

KNN is a non-parametric method for classification. It simply stores instances of the training data, and classify samples by a simple majority voting of the K-nearest neighbors. In this study, the parameter K is 7.

CART is a typical decision-tree model that can be used for both classification and regression tasks. In the training phase, the features for splitting data sample are determined by maximizing some predefined impurity measure. In this study, the 'Gini' coefficient is adopted to measure the impurity of the tree nodes. And the maximum depth of the tree is 4.

SVM is a method that seeks a best superplane to separate negative and positive examples. The best supper-plane is obtained by maximizing the distance between a series of support vectors (SV) and the super-plane. It is formulated as Eq2:

$$\hat{y} = \sum_{i \in SV} y_i \alpha_i K(x_i, x) + b \qquad (2)$$

Where $\hat{y}$, y_i, are predicted label and the label of the i[th] SV, respectively, α_i is the dual coefficient correspond to the i[th] SV, K is a kernel function. In practice, a number of kernel functions can be used in SVM. In this study, a 4[th] order polynomial kernel is adopted, and the regularization term is 1.0 in the loss function.

Logistic regression predicts the probabilities of an input by Eq3.

$$y = \frac{1}{1 + e^{-(w^T x + b)}} \tag{3}$$

Where w and b are the parameters that define the model, and can be estimated by the minimum square error criterion.

5.2 Results

Classification experiments are conducted to discriminate the MTD patients from the healthy subjects. For each task, 80% of the data is used for training, and the other 20% of the data is used for testing. Fig 4 presents the classification accuracy of different methods, namely, KNN, CART, SVM, and logistic regression, in both vocal and non-vocal tasks.

Since the purpose of this study is to explore the possibility of automatic diagnosis of MTD, we will focus on the classification accuracy of each task. As shown in Figure 4, the performance of different methods differs a lot in various tasks. If we choose 80% as the minimal acceptable accuracy of a classifier, KNN works properly in 4 tasks (THL, SW, PI, and HI), CART works properly in 4 tasks (THL, TC, HI, and LA), SVM works properly in 6 tasks (THL, TC, HI, HLI, LA, HLA), and Logistic regression works properly in 8 tasks (THL, THR, SS, TC, DB, LI, HLI, PA, HA, LA). The logistic regression method performs best on discriminating MTD patients from normal subjects in various vocal and non-vocal tasks.

For each vocal and non-vocal task, it is found at least one of the four classifiers can discriminate the MTD patients from the healthy ones with relatively high accuracies. In the non-vocal task THL, MTD patients can be recognized by all the four classifiers. In tasks TC, HI, and LA, the MTD patients can be recognized by three of the four classifiers. It indicates that MTD patients are easier to be recognized when conducting these vocal and non-vocal tasks.

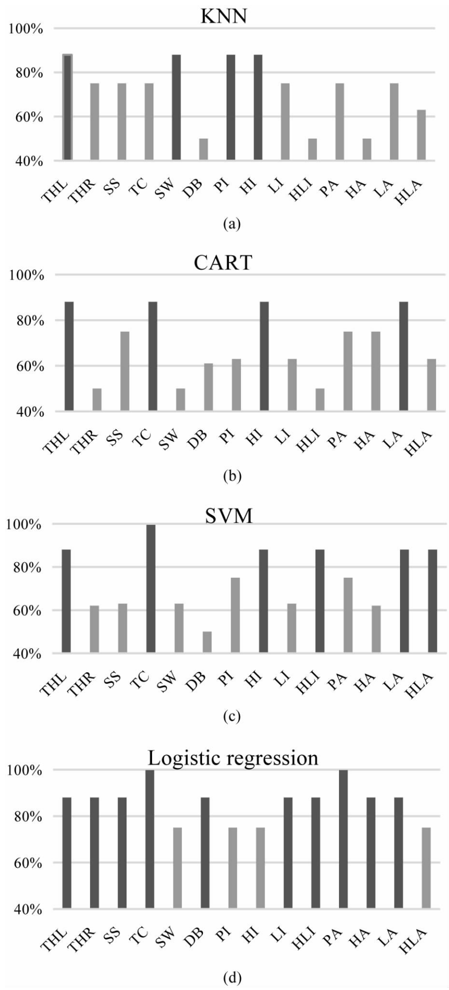

Figure 4 The precision of four classifiers for diagnosing MTD patients in various vocal and non-vocal tasks

6. DISCUSSION

In this study, we explore the possibility of automatic diagnosis of MTD based on task-related sEMG signals. To this end, the sEMG signal are collected and transformed to corresponding 850 time and frequency domain features. And Fisher' s F-ratio is adopted to select task-related features for automatic diagnosis. Four traditional classification methods (KNN, CART, SVM, and Logistic regression) are implemented to discriminate the MTD patients and normal people. It is found that the precision of discrimination can be as high as 80% if proper tasks and classification methods are chosen.

In this study, both vocal and non-vocal task show significant differences between the MTD patients and the healthy group, which is different from the results of Redenbaug and Reich' s work [14]. It is found that the MTD patients can be discriminated from normal controls with high accuracies by using Logistic regression method even for non-vocal tasks. This suggests that not only vocal tasks but also non-vocal tasks may be used in clinical practices. In the future, more data will be collected, and more advanced classifiers will be explored for tasks of discriminating MTD patients.

Acknowledgments

This work is supported by Special Program for Clinical Medicine Development of Beijing Hospitals Authority(XMLX201848).

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FANG Qiang Ph. D, associate professor of Institute of Linguistics, Chinese Academy of Social Sciences. His research interests include speech production and modeling.
Email: fangqiang@ cass. org. cn

[本文原载《中国语音学报》第17辑，2022年]