INVESTIGATION OF DISCRIMINATORY POTENTIAL IN ACCELEROMETRY SIGNAL FOR ABNORMAL SWALLOW DETECTION

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INTRODUCTION

Dysphagia (swallowing disorder) is a serious health problem that affects many people suffering from neurological impairments such as stroke, cerebral palsy, or Parkinson's disease. Abnormal swallows are likely to lead to airway invasion, and frequent deposition of foreign material in the lungs represents a dangerous situation that can result in aspiration pneumonia. Dire consequences of aspiration pneumonia include long-term hospitalization and even death [1].

Hence, abnormal swallow detection is an important aspect of today's dysphagia assessment. Videofluoroscopy, which records X-ray videos of the pharyngeal region during swallowing for analysis by speech-language pathologists, is the current gold standard in dysphagia assessment [2]. However, due to its limited availability and high cost, everyday dysphagia assessment is far from reality. Although several other detection techniques currently exist, none of them can adequately function as a portable diagnostic tool that can be easily used at home by caregivers or patients themselves.

In light of such a limitation, swallowing accelerometry [3] has shown potential in discrimination between healthy and abnormal swallows [4]. In this technique, an accelerometer is placed on the neck just below the thyroid cartilage to record skin surface vibration during swallowing. Various time and frequency domain features are extracted from the recorded accelerometry signals and a classifier is trained based on them.

In particular, we previously investigated swallowing accelerometry with a pediatric population with cerebral palsy recruited at Bloorview Kids Rehab [5]. In this previous study, a radial basis classifier resulted in a promising detection performance. In order to validate this technique with a different population with dysphagia, we collected accelerometry signals from adult patients with dysphagia at Toronto Rehabilitation Institute for our current study. Signals from 29 participants were included in this study, where 17 of them suffered from stroke.

OBJECTIVES

The objectives of this study were:

- to characterize the accelerometry signals via feature extraction and
- to investigate the existence of discriminatory information in the accelerometry signals by training a few simple classifiers.

METHODS

Data collection and signal segmentation

Accelerometry signals were collected at a sampling rate of 5 kHz during routine videofluoroscopy examinations. X-ray videos and accelerometry signals were acquired by two separate systems which were time-synchronized. Clinicians analyzed the videos and identified the onset and offset time indices for each swallow attempt. The onset and offset of a swallow were defined as when the bolus reaches the shadow of the mandible and when the hyoid comes back to its pre-swallow position. Then, these time indices were used to manually segment the accelerometry signals into corresponding swallow attempts. The segmented signals were further trimmed by listening to the accelerometry signals played as sound and identifying the parts with distinct swallow sound. Signals with poor signal-to-noise ratio were discarded.

The clinicians also labeled each swallow as one of the following depths of airway invasion: 0=no material entering the airway; 1=material penetrated the supraglottic space but remained above the vocal cords; 2=material penetrated the airway to the level of the vocal cords; 3=material was aspirated below the level of the true vocal cords. In this study, level 0 signals were designated as healthy swallows and levels 1, 2, and 3 comprised abnormal swallows. In the end, 91 healthy swallow and 15 abnormal swallow signals became available for analysis.

Denoising

All signals were lowpass filtered at 1.5 kHz by utilizing a digital 8^{th} order Butterworth filter in MATLAB.

Feature extraction

Five time-domain (stationarity, normality, dispersion ratio, zero-crossings, peak-to-peak amplitude) and three frequency-domain features (average power, maximum power, frequency at maximum power) were extracted from each signal. These are the features that previously showed promising discriminatory potential [4,5]. All the spectral features were extracted by utilizing the Fast Fourier Transform (FFT). For detailed computation steps of the time-domain features, please see [5].

Dimensionality reduction

Due to the curse of dimensionality, 106 samples are probably not enough to populate an 8-dimensional space. Furthermore, since there are only 15 abnormal swallow samples, a dimensionality greater than 2 cannot be justified when building even the simplest classifier. Hence, two classic dimensionality reduction techniques, namely principal component analysis (PCA) and linear discriminant analysis (LDA), were employed. Only the two dimensions corresponding to the two largest eigenvalues were kept, and classifiers were trained based on these two dimensions as well as only on the dimension that corresponded to the largest eigenvalue. As the scree plots of Figure 1 show, dimensionality reduction was effective for both PCA and LDA, with the largest eigenvalue representing almost 100% of the total eigenvalue sum.

Classifier models

Three simple classifier models were investigated: Bayesian, K-nearest neighbor (K-NN), and probabilistic neural network (PNN).

The Bayesian classifier was trained by fitting a bivariate (or univariate) Gaussian distribution to each class by finding the sample mean vector (or simply sample mean) and covariance matrix (or variance). Also, the conditional probability of the abnormal swallow class was weighted twice that of the healthy swallow class to reflect the fact that misclassifying an abnormal swallow is more costly than misclassifying a healthy swallow. The K-NN classifier was trained with K values of all odd integers from 1 to 15. Also, the Euclidean distance measure was utilized. Lastly, the PNN classifier was trained with a spread value of 0.1 for radial basis functions.

Performance measures

Performance was evaluated by three measures: zero-one loss error rate, sensitivity, and specificity. Sensitivity and specificity are defined as follows:

$$\text{Sensitivity} = \frac{\text{Number of correctly classified abnormal swallows}}{\text{Total number of abnormal swallows}}$$

$$\text{Specificity} = \frac{\text{Number of correctly classified healthy swallows}}{\text{Total number of healthy swallows}}$$

All three performance measures were computed by leave-one-out cross-validation.

RESULTS

Classification performance

Table 1 presents a complete set of the classification results. Generally, LDA outperformed PCA in all classifier models. Especially, all PCA-based classifiers resulted in poor sensitivities. All classifiers had trouble scoring high sensitivities and were relatively proficient in scoring high specificities. Also,

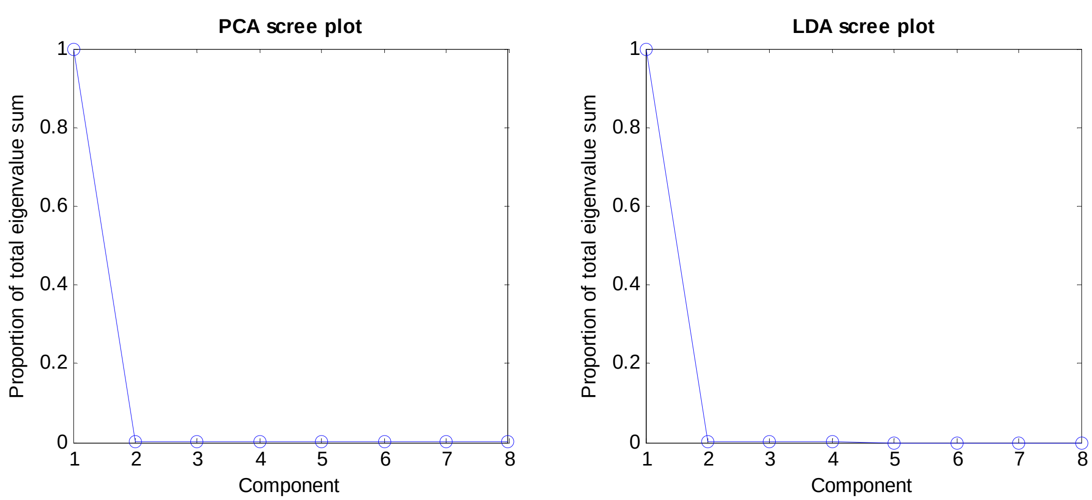

Figure 1: PCA and LDA scree plots

Table 1: Classification performance

			1-Dimensional	2-Dimensional
Bayesian	***Error Rate***	***PCA***	0.1415	0.1604
		LDA	0.0943	0.0943
	Sensitivity	***PCA***	0.2000	0.2000
		LDA	0.5333	0.6000
	Specificity	***PCA***	0.9670	0.9451
		LDA	0.9670	0.9560
K-Nearest Neighbor	***Error Rate***	***PCA***	0.1415	0.1415
		LDA	0.0849	0.1038
	Sensitivity	***PCA***	0.0000	0.0000
		LDA	0.5333	0.3333
	Specificity	***PCA***	1.0000	1.0000
		LDA	0.9780	0.9890
Probabilistic Neural Network	***Error Rate***	***PCA***	0.1415	0.1415
		LDA	0.1038	0.1132
	Sensitivity	***PCA***	0.0000	0.0000
		LDA	0.4000	0.3333
	Specificity	***PCA***	1.0000	1.0000
		LDA	0.9780	0.9780

the 1-dimensional classifiers tended to perform a little better than or as equally well as the 2-dimensional classifiers in general.

For the K-NN classifiers, the best K values were determined based on the lowest error rate. If several K values yielded the same lowest error rate, sensitivity and specificity were benchmarked next. If all three performance measures were identical, the smallest K value was chosen. This way, the optimal K values were 9, 9, 3, and 9 for the 1-D PCA, 2-D PCA, 1-D LDA, and 2-D LDA classifiers. The results shown in Table 1 are based on these optimal K values.

Overall, the 1-D LDA K-NN classifier resulted in the best performance. However, roughly speaking, the Bayesian classifiers performed as equally well as the K-NN classifiers. In particular, the 2-D LDA Bayesian classifier resulted in the best sensitivity of 0.6. The PNN classifiers performed slightly worse than other classifiers.

<u>Effects of dimensionality reduction</u>

Figure 2 shows the features of the signals projected onto a 2-dimensional space via PCA and LDA. It is apparent that PCA did not separate the two classes effectively, whereas LDA quite successfully clustered the healthy swallows together and placed most of the abnormal swallows as outliers.

DISCUSSION

The visible separation in the LDA plot of Figure 2 sheds promising light on the existence of discriminatory information in swallowing accelerometry signals. This discriminatory nature of the extracted features is reflected in the good performance results in Table 1.

The fact that most of the training samples were healthy swallows may have been at least partially responsible for the high specificities and low sensitivities. However, this imbalance between classes was the precise reason why such localized classifiers as K-NN and PNN were employed in this study. Hence, the effect of the imbalance should have been insignificant. Rather, the LDA plot of Figure 2 shows a well-structured cluster of healthy swallows and scattered abnormal swallows, and perhaps this implies that the classifiers should have easily learned the structure of the healthy swallows but not that of the abnormal swallows.

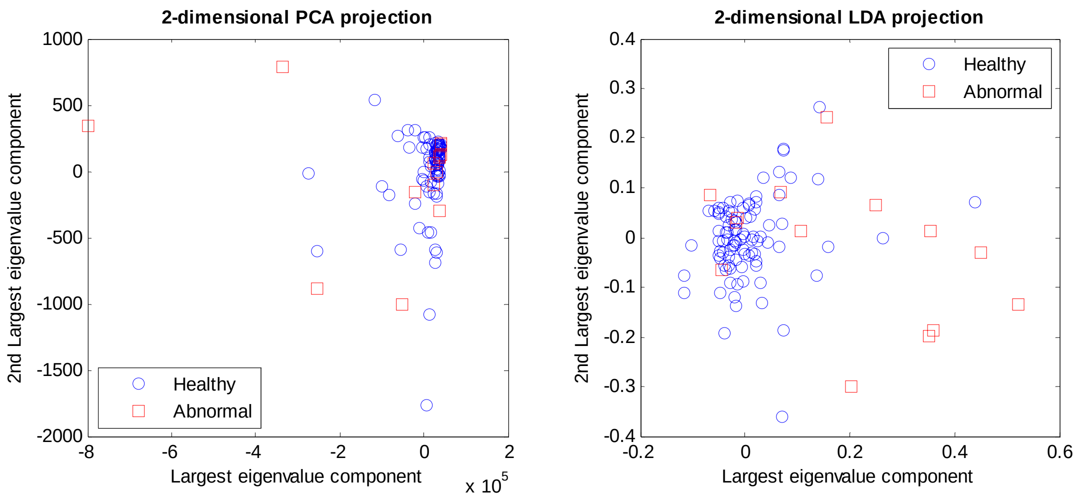

Figure 2: 2-dimensional PCA and LDA projection plots

It is possible to increase sensitivity at the cost of decreasing specificity. For instance, in the case of the Bayesian classifiers, the error of incorrectly classifying abnormal swallows as healthy swallows can be penalized more strongly.

LDA's superior classification performance to PCA comes at no surprise. LDA is designed to seek for a projection onto a lower dimensional space that maximizes between-class scatter but minimizes within-class scatter. On the other hand, PCA simply chases after a projection that captures the most variance in the data. In other words, LDA and PCA are supervised and unsupervised learning techniques, respectively. Thus, LDA is more suitable for classification applications.

CONCLUSIONS

The results of this study certainly suggest that the accelerometry signals collected from the adult population with dysphagia contain useful discriminatory information that can be used for abnormal swallow detection.

FUTURE WORKS

It would be worthwhile investigating other signal features than the 8 examined in this study. In addition, since healthy swallows seem to be associated with a well-characterized underlying structure, an attempt to model healthy swallows in terms of swallowing accelerometry signals seems to be reasonable. Lastly, signal segmentation was apparently a crucial step and a more systematic segmentation algorithm should be researched.

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