Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

A Radial Basis Function Classifier for Pediatric Aspiration Detection

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***Abstract*— Silent aspiration presents a serious health issue for children with dysphagia. To date, there is no satisfactory means of detecting aspiration in the home or community. In an effort to design a practical device that could offer reliability, non-invasiveness, portability, and easy usability, radial basis functions based on cervical accelerometry signals were investigated. Vibration signals associated with safe swallows and aspirations, both identified via videofluoroscopy, were collected from over 100 children with neurologically-based dysphagia using a single-axis accelerometer. Three time-domain discriminatory mathematical features were extracted from the accelerometry signals. An exhaustive set of all possible combinations of the features was investigated in the design of radial basis function classifiers. The feature pairing of dispersion ratio and normality achieved an accuracy of 81.03 ± 5.78%, a false negative rate of 9.06 ± 4.84%, and a false positive rate of 9.91 ± 5.03% for aspiration detection. The proposed classifier can be easily implemented in a hand-held device.**

I. INTRODUCTION

A. Dysphagia and Aspiration

Dysphagia generally refers to any swallowing disorder [1]. Impaired swallowing may result from mechanical disorders or anatomic abnormalities of the mouth, nose, pharynx, larynx, trachea and esophagus. Compromised swallowing function can also be neurological in origin. Disorders of deglutition are common in neurological impairments due to stroke, cerebral palsy or acquired brain injury.

Aspiration is entry of foreign material into the airway below the true vocal cords [1] accompanied by inspiration [2]. Approximately 25% of individuals at risk of aspiration do so in a "silent" manner [3] with no overt physiological signs, and the caregivers may have no warning that an aspiration has occurred.

B. Aspiration and the Pediatric Population

Children with dysphagia often have heightened risk of aspiration. Silent aspiration is especially prominent in children with dysphagia, occurring in an estimated 94% of that population [4]. The increased risk of aspiration bears serious health consequences such as dehydration, malnutrition, chronic lung disease and acute aspiration pneumonia [4], [5]. The latter is an expensive outcome that often requires extended hospitalization. Pulmonary aspiration can also evolve to include systemic complications such as bacteremia, sepsis, end-organ consequences of hypoxia, and even death [6]. Chronic aspiration is therefore an insidious problem that tremendously diminishes quality of life, not only compromising a child's physical, but social, emotional and psychosocial well-being.

C. Inadequacy of Current Aspiration Detection Techniques

1) Videofluoroscopy: The modified barium swallow using videofluoroscopy is the current gold standard for diagnosis of aspiration [7]. The patient ingests barium-coated material and a video sequence of radiographic images is obtained via X-radiation. This is costly both in terms of time and labor, and exposure to radiation limits frequency of its usage [8].

2) Fibreoptic Endoscopy: A flexible endoscope is transnasally inserted into the laryngopharynx. Although it has been utilized for bedside identification of silent aspiration [9], it is an invasive technique.

3) Pulse Oximetry: Although non-invasive, several controlled studies comparing pulse oximetric data to videofluoroscopic [10] and fibreoptic endoscopic evaluation [11], [12] have raised doubts about the existence of a relationship between arterial oxygen saturation and the occurrence of aspiration.

4) Cervical Auscultation: Listening to the breath sounds near the larynx is achieved by way of a laryngeal microphone, stethoscope, or accelerometer placed on the neck. However, when considered against videofluoroscopy, bedside evaluation with cervical auscultation yields limited accuracy in aspiration detection [13].

5) Accelerometry: This is closely related to cervical auscultation, but has entailed digital signal processing and artificial intelligence as discrimination tools, rather than the trained clinical ear. In clinical studies, accelerometry has demonstrated moderate agreement with videofluoroscopy in identifying aspiration risk [14] while the signal magnitude has been linked to the extent of laryngeal elevation [15].

D. Objective of This Study

No technique has stemmed from the above methodologies to completely satisfy the caregivers of dysphagic children in bedside setting. Their requirements are reliability, non-invasiveness, portability, and easy usability. In the light of this unmet need, we present a radial basis classifier for automatic detection of aspiration in children with dysphagia.

II. METHOD

A. Data Collection

One hundred and seventeen children suspected to be at risk of aspiration were recruited for data collection. The mean age of the participants was 6.0 ± 3.9 years with 64 males and 53 females. Swallowing difficulty in all the participants was neurological in origin, with the overwhelming majority having a primary diagnosis of cerebral palsy.

Lateral fluoroscopic video of the cervical region and accelerometry data were collected from each child during routine videofluoroscopic examination. A single-axis accelerometer was attached to the child, infero-anterior to the thyroid notch. The child was fed a barium-coated bolus of varying consistencies as per the modified barium swallow procedure. Although recorded separately, the video x-rays and the vibration signals were recorded in a time-synchronized manner. Fig. 1 illustrates the data collection setup.

The fluoroscopic video records were subjected to retrospective blind review by a committee of three to four clinical experts for the purpose of aspiration identification. The vibration signals associated with the identified instances of aspirations were carefully extracted and reviewed by the committee. Additional details of aspiration signal extraction can be found in [2]. By this procedure, 94 aspiration and 100 swallow signals were extracted.

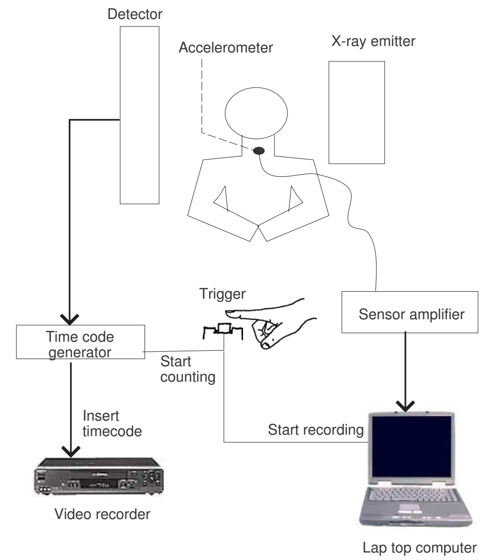

Fig. 1. Data collection setup for the simultaneous acquisition of time-synchronized videofluoroscopic and accelerometric data.

B. Feature Extraction

Stationarity, normality, and dispersion ratio provided statistically different unidimensional distributions for swallows and aspirations, by a rank sum test ($p \leq 8.5 \times 10^{-4}$ for each of the three features). Note that each of the three features can be considered as capturing time domain information.

1) Stationarity: Weak stationarity implies that the mean and variance of the signal do not change over time. The reverse arrangement test is a simple, non-parametric test for stationarity [16]. For convenience, we used the associated test statistic as the stationarity feature, that is,

$$z_A = \frac{A - \mu_A}{\sigma_A} \tag{1}$$

Here, A is the number of reverse arrangements in the signal, and μ_A and σ_A, defined as in [2], only depend on the length of the signal. Under the null hypothesis of stationarity, z_A is distributed as a standard normal with zero mean and unit variance. Hence, at the 5% significance level, $|z_A| < 1.96$ for a stationary signal. For a step-by-step procedure for calculating the number of reverse arrangements, A, please see [16].

2) Normality: Normality measures the adherence of a signal's amplitude distribution to that of an ideal normal distribution. Suppose we have a signal of length n. To compute this feature, the signal's amplitude is first divided into a finite number of intervals or bins, $I,\ I << n$, over the range of variation. We then count the number of times the signal's amplitude falls into each bin, yielding so-called observed frequencies. For each bin, we can also compute an expected frequency, that is the number of observations one would expect had the signal's amplitude been normally distributed. From these quantities, we derived a normality feature, N, on the basis of the Chi-square test for normality [17], namely,.

$$N = \sum_{i=1}^{I} \frac{(n_i - \hat{m_i})^2}{\hat{m_i}} \tag{2}$$

In the above, n_i is the observed frequency in the i^{th} bin, and $\hat{m_i}$ is the expected frequency in the same bin under the null hypothesis of a normal amplitude distribution.

3) Dispersion Ratio: Dispersion ratio is the ratio between the mean absolute deviation and the interquartile range of a signal. The mean absolute deviation, MAD can be found by,

$$MAD = \frac{1}{n} \sum_{i=1}^{n} |x_i - med(x)| \tag{3}$$

where n is the total number of samples in the signal, x_i is the i^{th} sample of the signal, and $med(x)$ is the median of the signal. The interquartile range, denoted here as IQR, is defined as

$$IQR = q_{0.75} - q_{0.25} \tag{4}$$

where $q_{0.25}$ and $q_{0.75}$ are the first and third quartiles of the signal's amplitude distribution. The dispersion ratio is expressed as,

$$D = \frac{MAD}{IQR} \tag{5}$$

and can be interpreted as capturing the difference between a non-robust (mean absolute deviation) and a robust (interquartile range) estimate of spread. This feature thus roughly reflects the nature and multiplicity of atypical observations within the signal. In the absence of such atypical observations, the ratio would tend to unity. For further details about the constituent computations for this feature, please see for example [18].

TABLE I

PERFORMANCE COMPARISON OF ALL POSSIBLE FEATURE COMBINATIONS

Combination	**Accuracy (%)**	**False Negative Rate (%)**	**False Positive Rate (%)**
D	70.94 $\pm$ 6.11	13.42 $\pm$ 4.93	15.64 $\pm$ 5.48
N	66.15 $\pm$ 7.75	10.94 $\pm$ 6.13	22.91 $\pm$ 8.73
S	61.54 $\pm$ 6.83	20.43 $\pm$ 5.81	18.03 $\pm$ 6.00
D-N	81.03 $\pm$ 5.78	9.06 $\pm$ 4.84	9.91 $\pm$ 5.03
D-S	64.62 $\pm$ 7.36	16.75 $\pm$ 5.90	18.63 $\pm$ 6.42
N-S	78.12 $\pm$ 5.38	13.59 $\pm$ 5.27	8.29 $\pm$ 3.67
D-N-S	78.46 $\pm$ 5.93	12.99 $\pm$ 5.17	8.55 $\pm$ 3.52

C. Radial Basis Classifier Design

A radial basis function network, a highly versatile and easily implementable classifier, was chosen to facilitate the selection of decisive features. The radial basis function network is a universal function approximator [19]. In other words, given sufficient training samples and unlimited hidden units, the network is able to model any continuous function between the inputs and outputs.

For our experiments, the number of inputs to the network equaled the number of features, ranging from 1 to 3. The network had a single output with a numerical value of either 0.9 or 0.1 for aspirations and swallows, respectively. The gaussian radial basis function was selected for its proven approximation capabilities. The number of radial basis units was increased as necessary during training to achieve the targeted performance. Initially, all networks started with two basis units and this was increased by five at each training iteration to a maximum equal to the number of training exemplars. The termination criterion for training was a successive error of 0.1. This coarse error margin was considered sufficient since our target values of 0.1 and 0.9 can be resolved at this precision. The output function can be written as a linear summation of the gaussian kernels evaluated at the current input vector, $\mathbf{x}$,

$$f(x) = \sum_{i=1}^{M} w_i G(||\mathbf{x} - \mathbf{c}_i||) \tag{6}$$

where w_i is the weight from the i^{th} radial basis to the output layer, $G(\cdot)$ is the radial basis kernel, $\mathbf{c}_i$ is the center of the i^{th} radial basis function and $|| \cdot ||$ denotes Euclidean distance. In our case, we have $\mathbf{x} = [SND]^T$, where S=stationarity, N=normality, and D=dispersion ratio. The simulation experiments were conducted in MATLAB.

D. Evaluation of Feature Sets

To identify which combinations of the features yielded the best discriminatory potential with a radial basis classifier, we exhaustively formed all possible unique combinations of feature set sizes from one to three. In total, there were $\sum_{m=1}^{3} C(3,m) = 7$ unique feature combinations, where $C(n,m)$ means n choose m combinations . For each feature combination, we performed a hold-out estimate of various classification performance measures described in the next section. The 80%-20% split was deemed to provide a reasonably sized test set based on the sample size of available data (100 swallows + 94 aspirations = 194 instances).

E. Classifier Performance Measures

Positive and negative detections refer to classification decisions of aspirations and swallows, respectively. Therefore, a false positive (FP) is the event of classifying a vibration signal as an aspiration when a swallow has actually occurred, whereas a false negative (FN) is the event of classifying a vibration signal as a swallow when an aspiration has actually occurred. Likewise, an aspiration that is correctly classified as such is a true positive (TP) and a correctly classified swallow is a true negative (TN). The most common measure of classifier performance is accuracy, defined as

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

where the denominator is simply the total number of attempted classifications. False negative rate is the proportion of the total number of attempted classifications that is false negatives, and is defined as

$$\text{False Negative Rate} = \frac{FN}{TP + FP + TN + FN} \tag{8}$$

False negative rate is a crucial measure because it indicates how often aspirations are not detected, thus failing to notify the caregiver. Such a situation is directly related to health risk of the dysphagic child. False positive rate is the proportion of the total number of attempted classifications that is false positives, and is defined as

$$\text{False Positive Rate} = \frac{FP}{TP + FP + TN + FN} \tag{9}$$

False positive rate indicates how often the classifier gives a false alarm. Although it is not as significant as false negative rate in terms of the child's health, a high false positive rate degrades practicality of the classifier. Clearly, for both false negative and positive rates, the lower the better.

III. RESULTS

The classification results of all possible feature combinations are tabulated in Table I. The initials stand for S=stationarity, N=normality, and D=dispersion ratio. Considering accuracy and false negative rate to be more important than false positive rate, the duality of normality and dispersion ratio resulted in the best overall performance with an accuracy of $81.03 \pm 5.78\%$, a false negative rate of $9.06 \pm 4.84\%$, and a false positive rate of $9.91 \pm 5.03\%$. The achieved accuracy is 30% higher than those reported for bedside cervical auscultation.

IV. DISCUSSION

The proposed radial basis function classifier can be easily implemented in portable electronic hardware. Since all three features are time-domain parameters, the designed classifier would be particularly amenable to implementation on a standard workhorse microcontroller as all computations can be made in the time domain, in real-time. A prototype of the hardware implementation of the proposed classifier, named the "aspirometer", has already been built and is currently under development at Bloorview Research Institute.

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

The proposed pediatric aspiration classifier provides promising accuracies. Dispersion ratio and normality prove to be especially good features for distinguishing aspirations from safe swallows. Most importantly, this classifier can be implemented in a hand-held device without difficulty. The caregivers of silently aspirating children can benefit from such a device with minimal training.

B. Future Works

Further research into other discriminatory features than the three considered and other, possibly simpler, classifiers may result in even better accuracy, false negative rate, and false positive rate. Also, it should be noted that the current classifier is based on vibration signals of which the physiological origin has not been clearly identified. Addition of other physiological data such as respiration or muscle activity may add more convincing physiological reasoning to the results while further improving the aspiration detection performance. Additionally, the current results have been obtained only with pediatric data and cannot be generalized to adults. Future studies on adults employing similar methodology are required to ascertain the generalizability of automatic aspiration detection using the proposed features and classifier.

VI. ACKNOWLEDGMENTS

The authors would like to acknowledge funding from the University of Toronto (JL), Natural Sciences and Engineering Research Council (TC), Canada Research Chairs Program (TC), Bloorview Childrens Hospital Foundation (DK, MC, GB) and Rani Ghar Grotto Cerebral Palsy Foundation (DK, MC, GB). We are also indebted to the families and children who participated in the many months of data collection. TC would also like to acknowledge useful discussions with Catriona Steele and Pascal van Lieshout about clinical applications of the aspirometer.

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