Technical Notes

Investigating the Stationarity of Paediatric Aspiration Signals

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***Abstract*—An aspiration signal is the time-varying anterior–posterior acceleration measured infero–anterior to the thyroid notch when foreign material enters the airway during inspiration. The hypothesis of weak stationarity is tested on aspiration signals by the reverse arrangements test. Results indicate that aspiration signals cannot be uniformly regarded as weakly stationary. Forty-five percent of the examined signals violated the stationarity hypothesis. For these signals, time-varying variance and spectral density structure are identified as major sources of nonstationarity. Stationarity test results generally corroborate qualitative clinical descriptions of aspiration. However, stationarity analysis indicates that aspiration signals are highly heterogenous, a finding which poses significant challenges to the automatic detection of aspirations by accelerometry.**

***Index Terms*—Accelerometry, aspiration, dysphagia, reverse arrangements test, test of stationarity.**

I. Introduction

A. Aspiration

Dysphagia refers to any deglutition (swallowing) disorder, including abnormalities within the oral, pharyngeal, and esophageal phases of swallowing [1]. Dysphagia is common in individuals with neurological impairment, due to, for example, cerebral palsy, cerebrovascular accident, brain injury, Parkinson's disease, stroke, and multiple sclerosis (see, e.g., [2]–[4]). Individuals with dysphagia are often at risk of aspiration. Aspiration is defined as the entry of foreign material into the airway during inspiration. Silent aspiration is aspiration that is not associated with a cough response in alert and awake individuals [5]. Aspiration bears serious health consequences such as dehydration, malnutrition, chronic lung disease, and acute aspiration penumonia [6], [7].

For clarity, we distinguish swallows and penetrations from aspirations. A swallow is understood to be the safe passage of foodstuffs from the oral cavity, through the hypopharynx and into esophagus. Further, a swallow is accompanied by a period of apnea [8] with no entry of foodstuff into the protected airway [9]. Penetration is the entry of foreign material into the airway but not accompanied by inspiration. Textbook definitions of aspiration and penetration often distinguish between the two according to the level of descent of the foreign material [10]. In our opinion, the broader definitions adopted here provide a more realistic assessment of aspiration risk in children and fits more closely with the pathophysiology and treatment of aspiration. As aspirations often connote greatest clinical risk, this paper focusses exclusively on the stationarity of aspiration signals, postponing the study of penetrations and swallows, as defined earlier, for future research.

Manuscript received January 7, 2003; revised September 12, 2004. This work was supported by the Bloorview Childrens Hospital Foundation, the Hospital for Sick Children Foundation, and the Natural Sciences and Engineering Research Council of Canada.

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Digital Object Identifier 10.1109/TNSRE.2004.841384

B. Detection of Aspiration

Currently, rehabilitative management of dysphagia includes postural adjustment while feeding, oral sensory enhancement techniques such as thermal-tactile stimulation, modifying volume, and speed of food presentation and altering food consistency [11]. The identification of aspiration is critical to rehabilitation planning for the individual with dysphagia. Numerous aspiration detection technologies along with accompanying clinical screening procedures have been proposed in the literature (see [1] for a review), including, for example, fiberoptic endoscopy [12], pulse oximetry [13], electroglottography (EGG) [14], cervical auscultation with pharyngeal microphone [15], and the present-day gold standard, the modified barium swallow using videofluoroscopy [10]. There is, however, a practical need for a noninvasive, economical, and portable method for detecting aspiration [16] at the bedside and outside of the institutional setting.

C. Accelerometry

In recent years, there has been a keen interest in the application of accelerometry for the assessment of swallowing function [16]–[20]. Accelerometry refers to the noninvasive measurement of epidermal mechanical vibrations associated with swallowing [21]. Measurement is usually by way of a miniature accelerometer placed at the skin surface in the general vicinity of the thyroid cartilage. The accelerometry of swallows has been studied considerably, for example, in the classification of pathological swallows [16] and the characterization of the pharyngeal phase of swallowing [20]. In contrast, little has been done to systematically characterize aspiration signals. This may be attributed to the difficulty of collecting an adequately sized sample of signals, especially from the paediatric population, where the occurrence of clinical aspirations is relatively rare.

D. Goal of Note

The goal of this technical note is to test the stationarity hypothesis on the acceleration time-series associated with aspiration events. The hypothesis of stationarity seems reasonable given previous reports that aspiration signals resemble "noise" [18] and the prevalent assumption of local stationarity in short duration physiological signals, such as electromyograms [22] and event-related electroencephalograms [23]. Stationarity is a fundamental characteristic of random data [24]. The presence or absence of stationarity often impacts the choice of analysis methods, such as in the characterization of fractal structure in temporal physiological signals [25]. In the context of aspiration detection, the results of stationarity assessment will determine the class of suitable automatic classification methods.

Section II reviews the definition of a stationary time series and outlines a nonparametric test of stationarity. Section III outlines the experimental methodology for data collection, isolation of aspirations, and stationarity testing. In Section IV, results of stationarity testing on aspiration signals are presented. This note closes with a brief discussion of the clinical and analytical implications of stationary and nonstationary aspirations.

II. Stationarity

A. Stationary Time Series

Let X_t denote a real-valued random variable representing the observation made at time t. We shall assume that observations are made at regular intervals and without loss of generality, index the observations by integers, i.e., $t \in \mathbf{I}$, where $\mathbf{I}$ is the set of integers. We adopt the following definition of a time series [26].

Definition 1: A time series $\{X_t\}$ is a family of real-valued random variables, where $t \in \mathbf{I}$ and $\mathbf{I}$ denotes the set of integers.

Strictly speaking, the commonly encountered definition of stationarity applies only to the abstract generating process (for example, see [27]) and not to some realization that produces a time series [28]. However, for the purpose of this paper, we will adopt the practical notion of a stationary time series as defined in [26].

Definition 2: A time series $\{X_t\}$ is strictly stationary if, for any, $t_1, t_2, \ldots, t_n \in \mathbf{I}$, any $c \in \mathbf{I}, n = 1, 2, \ldots$, the distribution function is invariant to a shift in the origin, i.e.,

$$F_{X_{t_1}, X_{t_2}, \ldots, X_{t_n}}(x_1, x_2, \ldots, x_n) = F_{X_{t_1+c}, X_{t_2+c}, \ldots, X_{t_n+c}}(x_1, x_2, \ldots, x_n) \quad (1)$$

where the lower case symbol x_i denotes the realization of the random variable X_{t_i}. In this notation, $\{x_1, \ldots, x_n\}$ is thus a realization of a time series. The above definition is also referred to as strong stationarity as opposed to weak stationarity or wide-sense stationarity, in which, only the first two moments of the series are required to be time-invariant.

Definition 3: A time-series is weakly stationary if for any $t_1, t_2, c \in \mathbf{I}$,

$$E(X_{t_1}) = E(X_{t_1+c}) \quad (2)$$

and

$$\mathrm{Cov}(X_{t_1}, X_{t_2}) = \mathrm{Cov}(X_{t_1+c}, X_{t_2+c}). \quad (3)$$

Most time series analysis, linear or nonlinear, require some kind of stationarity [28]. Analysis procedures for nonstationary data are generally more complicated than those for stationary data [24]. Through simple transformations such as differencing [29] or polynomial trend removal [24], a nonstationary signal may be rendered stationary and compatible with many conventional analyses. Therefore, the verification or refutation of the stationarity hypothesis is critical to the choice of analysis methodology.

B. Stationarity Test: Reverse Arrangements Test

Numerous tests of stationarity have been proposed in the literature. These include for example, the autocorrelation test [30], the Runs test [31], unit root tests [32], surrogate data analysis [33], nonlinear cross predictions [34], and more recently, a wavelet-based test [35]. In this note, we deploy the reverse arrangements test, a general nonparametric test for weak or wide sense stationarity [24]. A widely used and time-honored procedure, the reverse arrangements test has been recently employed in evaluating the stationarity of physiological [22] and atmospheric signals [36]. The test is also known as the inversion test [36] and originally as the trend test [37]. The procedure is summarized in the following. Consider the realization $\{x_1, x_2, \ldots, x_N\}$ of a time series as defined previously.

1) Divide the sample record into M equal, nonoverlapping intervals, $I_i, i = 1, \ldots, M$, where the data in each interval can be considered as independent. This implies that within the selected interval, the data do not exhibit any obvious trends (e.g., monotonic increase). In practice, independence within each interval can be easily checked by statistically comparing the count of direction changes in the signal segment against that expected from an equivalently sized, data set of independent samples from a uniform random distribution.
2) For each interval, compute the mean square value, i.e., $y_i = (1/n)\sum_{k \in I_i} x_k^2$, where n is the number of points within each interval.
3) Count the total number of reverse arrangements A in the sequence $\{y_i, i = 1, \ldots, M\}$. A reverse arrangement occurs when $y_i > y_j$ for $i < j$.
4) Compare the value of A to that expected from a realization of a stationary random process. For a stationary time series, the number of reverse arrangements will be as expected for independent observations of a random variable. In such case, the distribution of A is approximately normal with mean $\mu_A = N(N-1)/4$ and variance $\sigma_A^2 = N(N-1)(2N+5)/72$ [37]. The null hypothesis that $\{y_i\}$ is stationary is rejected at significance level α if A falls outside the corresponding critical values.

To determine critical values, we can equivalently formulate the earlier test against a standard normal by writing

$$z_A = \frac{A - \mu_A}{\sigma_A} \quad (4)$$

where $z_A \sim N(0,1)$ is the test statistic and μ_A and σ_A are the mean and standard deviation as defined previously. The critical values at significance level α are then $z_{1-\alpha/2}$ and $z_{\alpha/2}$ where z is a standard normal variate. We will refer to z_A as the stationarity test statistic.

The value of the stationarity statistic z_A can fall into one of three ranges. These are interpreted as follows.

$z_A \geqq z_{\alpha/2}$. There are fewer reverse arrangements than expected of a stationary signal, implying the presence of an upward trend in the mean square sequence.

$z_A \leqq z_{1-\alpha/2}$. The number of reverse arrangements exceeds that expected of a stationary signal, implying a downward trend in the mean square sequence. Again, the signal is deemed nonstationary.

$z_{\alpha/2} < z_A < z_{1-\alpha/2}$. The signal is stationary.

For a 5% significance level, we have $z_{\alpha/2} = -1.96$ and $z_{1-\alpha/2} = 1.96$ for a standard normal deviate.

Note that the mean square value captures the first two moments of the time series, through the equation $E(X^2) = \mathrm{Var}(X) + E(X)^2$. Hence, in the reverse arrangements test, stationarity of the mean square sequence, $\{y_i\}$, implies weak or wide sense stationarity of the time series realization $\{x_i\}$ [24].

III. Methodology

A. Signal Measurement

One hundred and seventeen children suspected to be at risk of aspiration participated in this study. The mean age 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. All children had been experiencing swallowing difficulties since birth. A single-axis accelerometer (Siemens EMT 25C) was placed infero–anterior to the thyroid notch. The accelerometer converted mechanical vibrations into corresponding voltage fluctuations. The axis of acceleration was aligned to detect anterior–posterior vibrations. The child was fed a natural bolus of graduated consistencies mixed with barium. The amplified acceleration signal was digitally recorded by a portable computer (MacIntosh PowerBook G3, 266 MHz) in real-time, via a data acquisition unit (Biopac, model MP100), at a sampling rate of 10 kHz. The lateral X-ray videos (General Electric X-ray System, RFX-90) and acceleration signals were also simultaneously recorded onto a continuously time-stamped (FORA video timer, model VTG-55) analog audio-video tape (Panasonic VCR, model AG-6200). The initiation of both analog X-ray video and digital acceleration recordings was triggered by a common single-pole, double-throw pushbutton switch. Consequently, analog and digital records were perfectly synchronized in time. For each bolus consistency, a new recording segment was created. The time-stamp on the video segment and the time scale of the digital segment both reflected the time-elapsed since the most recent trigger. The absolute video time index at the beginning of each segment, indicating the time-elapsed since the beginning of the tape, was recorded manually. The synchronization of recording segments facilitated the isolation of aspiration described in the following.

B. Isolation of Aspirations

Aspiration events were isolated and verified in four steps.

Step 1) Initially, during the actual data collection session, a paediatrician specialist in clinical nutrition and videofluoroscopic identification of aspirations noted the approximate time of occurrence of candidate aspirations based on the dynamic X-ray video. These times were recorded for later reference.

Step 2) The videos pertaining to the candidate aspirations were reviewed by a committee, consisting of two paediatric dentists, a speech language pathologist, and a pediatrician. Based on video verification, the committee decided to accept or reject each candidate aspiration. The time intervals of the retained candidate aspirations were revised as necessary.

Step 3) The exact digital segment corresponding to each candidate aspiration was extracted from the digital accelerometry recordings. Due to synchronization of analog video and digital accelerometry records, this was a straightforward exercise.

Step 4) Finally, the isolated digital clips were presented before the committee for audio verification and final cross-referencing with video data. Aspirations with poor audio discernibility as judged by the clinically trained ear were discarded.

By this procedure, an aspiration signal thus began at the moment when aspiration was observed on videofluoroscopy, i.e., when the bolus entered the airway during inspiration. The aspiration signal ended at the conclusion of the inspiratory sound. Through the above process, 94 aspirations were isolated from the data on 23 children.

C. Stationarity Testing

It is known that the assessment of stationarity is dependent on window size [38]. Published studies on the spectral analysis of swallowing sounds have reported frequency content ranging from about 100 Hz [39] to several kilohertz [40], suggesting window sizes from fractions of a millisecond to tens of milliseconds. In this study, we determine a lower bound on the window size by roughly estimating the dominant low frequency band in terms of energy distribution. Each aspiration signal was subjected to a five-level discrete wavelet decomposition [41] using the Daubechies wavelet (Daub4) [42]. The energy at each level of decomposition was estimated by computing the sum of the square of the detail coefficients. At the last level, the energy in the approximation signal was also computed. It was found that over half of the aspiration signals (54%) retained the majority of their signal energy below 625 Hz. This implies that we require at least a window of 1.6 ms in duration to capture any periodic components at this frequency. Bendat and Piersol [24] recommend that the window length should exceed the period of the most slowly evolving (lowest frequency) periodic component of the signal. As a conservative estimate, we, therefore, require that the window size be at least 5 ms, that is, more than three times as long as the minimum 1.6-ms duration. We further constrain the number of windows to be at least 10, as a general rule of thumb for estimating a single statistical parameter (the number of reverse arrangements A, in this case). With these prescriptions in mind, we performed the stationarity test using window lengths between 50 and 100 data points, corresponding to temporal windows of 5 to 10 ms, given the 10-kHz sampling rate and average aspiration duration of 240 ± 122 ms. Since the signal lengths were in general not integral multiples of the chosen window sizes, we omitted a number of points less than the window size from both ends of the signals. To test if there was an effect of omitting specific points, we also repeated the tests omitting only points at the beginning and again omitting only points at the end.

D. Investigating Sources of Nonstationarity

For signals which violated the stationarity hypothesis, we further investigated some fundamental sources of nonstationarity [24], including time-varying mean, variance, and frequency content. For each identified nonstationary signal, we divided the time series into nonoverlapping windows and computed the mean, variance, and median frequency of the power spectral density within each window. Using regression analysis, we then tested the null hypotheses that each of these statistics varied over time according to a least-squares line with zero slope. In other words, we tested the time-invariance of the mean, variance, and median frequency for each nonstationary aspiration signal. Numerous parameters could be extracted from the power spectral density to characterize evolution over time. We chose the median frequency as a simple but robust location estimator [43].

IV. Results and Discussion

A. Clinical Correlates of Aspiration Signal Stationarity

Different children aspirated at different bolus consistencies, ranging from thin to thick liquids, and from thin to thick purées. In fact, stationarity test statistic values appear to be a fundamental characterization of aspirations signals, being statistically uncorrelated to age ($r = -0.25$), gender ($r = -0.067$), and bolus consistency ($r = -0.041$), as measured by the correlation coefficient r.

B. Effect of Window Size

Fig. 1 is a box plot showing the distribution of stationarity test statistic values z_A for each window size. The corresponding medians and interquartile ranges of z_A are reported in Table I. For windows longer than 9 ms in duration, some signals are not long enough to guarantee the minimum ten segments for stationarity testing. Hence, 9 ms is taken as the upper limit of window length. We notice that the median value of the stationarity test statistic, falls within the stationary range, at the 5% significance level, i.e., $|z_A| < 1.96$, and is essentially constant for the chosen window sizes. Indeed, using a Kruskal–Wallis test, we find that, overall, the stationary test statistic values are not significantly different among window sizes ($p = 0.99$). Hence, the stationarity statistic alone does not suggest a preferred window size.

Table I indicates that the number of nonstationary signals and the spread (interquartile range) of the stationary statistic across signals both tend to decrease with increasing window size. The latter is also evident from the progressively shortening of the boxplot whiskers in Fig. 1. At larger window sizes, a given signal is divided into fewer intervals, resulting in a shorter mean-square sequence. For a mean-square sequence of length N, the maximum number of unique reverse arrangements is $(N - 1)N/2$. Therefore, when the aspiration signals are parameterized into shorter mean square sequences, there are fewer possible

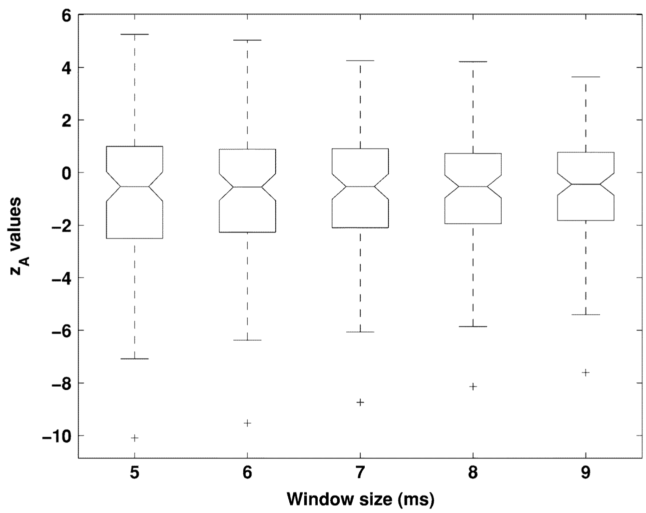

Fig. 1. Effect of window size on the stationarity test statistic values z_A computed for 94 aspiration signals.

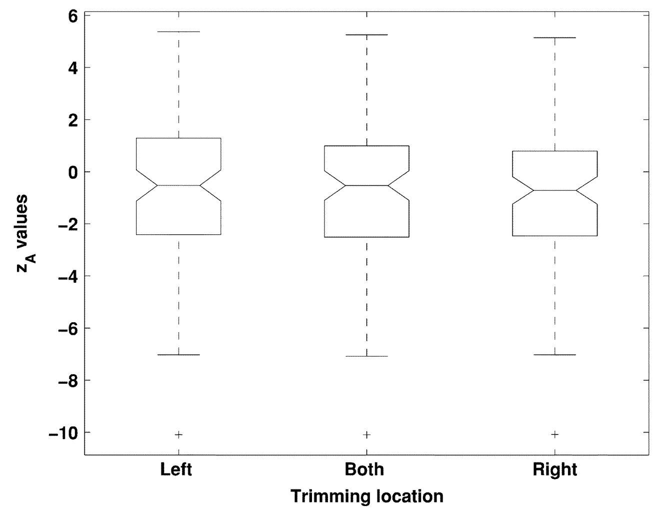

Fig. 2. Effect of signal trimming location on stationarity test statistic for a constant window size of 5 ms (window length $W = 50$ points). "Left" and "Right" refer to trimming at the beginning and at the end of the signal, respectively, by an amount $N \bmod W$, where N is the length of the signal. "Both" refers to trimming from both the beginning and end of the signal, each by an amount $\lfloor (N \bmod W)/2 \rfloor$.

TABLE I
STATIONARITY TEST RESULTS AT DIFFERENT WINDOW SIZES

Window length	# nonstationary (% of total)	z_A median	z_A IQR	No. segments for testing
5 ms	42 (44.7%)	-0.533	3.5	47 ± 24
6 ms	39 (41.5%)	-0.554	3.2	39 ± 20
7 ms	35 (37 %)	-0.536	3.0	34 ± 17
8 ms	31 (33 %)	-0.533	2.7	29 ± 15
9 ms	32 (34 %)	-0.448	2.6	26 ± 14

IQR = interquartile range; z_A = stationarity test statistic

TABLE II
PERCENTAGE OF SIGNALS THAT VIOLATE EACH HYPOTHESIS OF TIME-INVARIANCE

Statistical hypothesis tested	% of signals violating hypothesis (p=0.05)
Stable mean	5%
Stable variance	76%
Stable frequency	62%

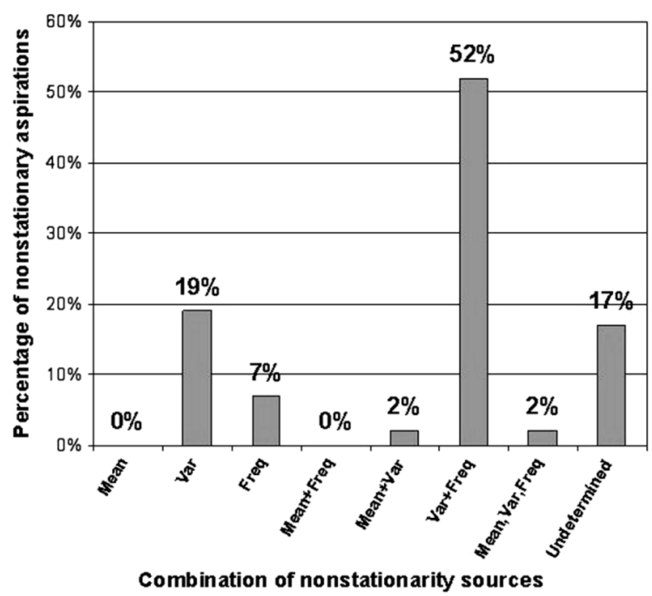

Fig. 3. Combinations of contributing sources of nonstationarity for the 42 nonstationary aspirations. Variance and frequency are abbreviated as "Var" and "Freq," respectively. The last column represents nonstationary signals that did not exhibit nonstationary mean, variance, or frequency.

variations in the number of reverse arrangements among signals. A reduction in the intersignal variability of z_A implies convergence of z_A values toward the median and, hence, fewer signals are classified as nonstationary. This finding agrees with intuition, namely, that with a sufficiently long window of observation, even a slowly varying trend will appear stationary.

At the largest window sizes, we also have the shortest mean square sequences and, hence, the least reliable estimate of the reverse arrangements statistic. Hence, a window length of 5 ms is deemed to be the most reliable as the stationarity tests for all signals at this window size are based on 18 or more segments. Thus, all subsequent results will be based on window lengths of 5 ms.

C. Effect of Trimming Location

Fig. 2 summarizes the distribution of stationarity statistic values obtained by trimming the aspiration signals at different locations. Using a one-way analysis of variance, we determine that stationarity statistic values (z_A) are not significantly influenced $(p = 0.9)$ by the choice of signal trimming. Hence, we arbitrarily choose to trim symmetrically from both ends of each aspiration signal.

D. Sources of Nonstationarity

The results of testing the time-invariance of mean, variance, and frequency structures for the 42 nonstationary signals are summarized in Table II. Clearly, the majority of nonstationarities are due to temporally unstable variance and/or frequency. To delve further, we categorize each signal according to the combination of contributing nonstationary sources. Fig. 3 enumerates the number of signals in each category. The combination of nonstationary variance and frequency accounts for over

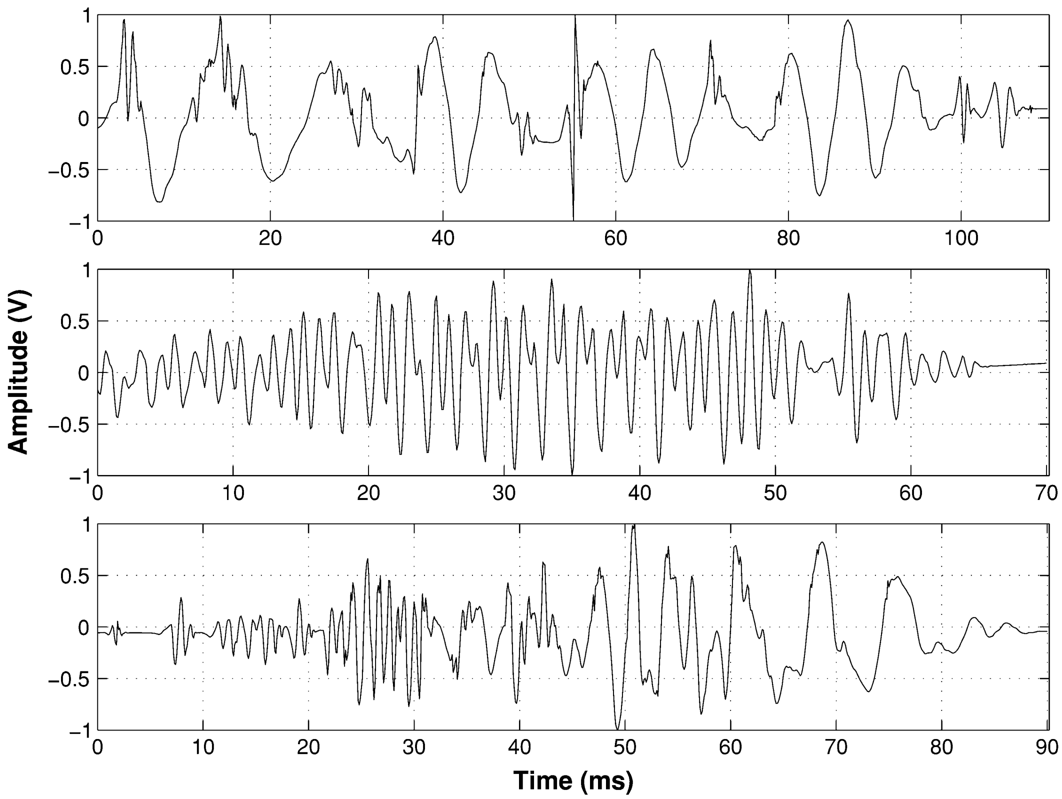

Fig. 4. Typical paediatric aspiration signals portraying (top graph) weak or wide-sense stationarity, (middle graph) nonstationarity due to evolving variance, and (bottom graph) nonstationarity due to time-varying frequency and variance structure.

half of the nonstationarity signals. In practical terms, this majority subgroup of nonstationary aspirations are "sounds" which are changing both in volume and pitch over time. About a fifth of the nonstationary signals owe their nonstationarity to evolving variance alone while another 7% are nonstationary strictly due to dynamic frequency content. The former can be understood as aspiration signals which only change in volume while the latter are signals which only change in pitch. Fig. 4 exemplifies some typical paediatric aspiration signals. The top graph is a stationary signal with relatively stable mean and variance. In contrast, the middle graph illustrates nonstationary variance over time, with a notable crescendo in the first part of the signal. In addition to fluctuating variance, the bottom graph portrays time-varying frequency content, with high frequencies in the first half of the signal followed by predominantly lower frequency structure in the latter half. Note that for 17% of the nonstationary signals, nonstationarity cannot be explained by time-varying mean, variance, or frequency. The reverse arrangements test may conclude that these signals are nonstationary as a result of inherent nonlinearities, such as self-similarity [44]. Further investigation into possible fractal structure in aspiration signals is warranted.

E. Implications of Stationarity and Nonstationarity

About 55% of the aspiration signals tested positive for weak stationarity. To the human ear, these sounds exhibit consistent volume and pitch over time, akin to random noise. It is this flavor of aspirations that was likely reported by Reddy *et al.* [18] as being unstructured and noise-like. The finding that over one in two aspirations are weakly stationary may explain why aspiration detection by cervical auscultation yields no better than 60% accuracy, even with the trained clinical ear. The stationary aspirations may represent silent aspirations or at least those without the clinically familiar high-frequency squeak.

Nonstationarity implies that many aspiration signals resemble speech, an inherently nonstationary sound, rather than flat-spectrum breath sounds. Indeed, the time-varying frequency and variance structures in over half the nonstationary aspirations may be due to an aberrant usage of the vocal cords as the bolus passes the vocal folds during inspiration. This flavor of nonstationarity may explain the often-described high-frequency squeak that accompanies clinical aspiration.

If, indeed, a class of aspirations can be likened to speech, then as in speech signals, there may actually exist some "speaker"-independent characteristics in aspiration sounds. The identification of such invariant characteristics would greatly aid automatic aspiration detection. However, note that this type of nonstationary signal represents less than a quarter of all aspirations in the present study.

In the reverse arrangements test, the majority of nonstationary signals are characterized by $z_A <= z_{\alpha/2}$, suggesting the presence of an increasing trend in the mean square sequence. Since the mean is temporally stable for most signals, we can infer from Table II that this mean square trend is due to an increasing variance over time. This finding echoes clinical observations of an audible "crescendo" effect in many aspiration sounds.

From the standpoint of signal analysis, the prevalence of nonstationary aspirations implies that it is necessary to routinely test signal stationarity prior to the choice of analysis methodology. Due to the large proportion of nonstationary signals, time-frequency methods such as the wavelet transform [41], are recommended for the extraction of classification features from aspiration signals. Application of methods, such as Fourier analysis, relative dispersion analysis [45], or time series regression [46], which inherently assume stationary signals, may lead to unreliable or misleading results.

These results suggest that typical temporal or spectral features may have limited discriminatory power in automatic aspiration detection. First, easily discernible, high frequency aspirations represent a much smaller fraction of aspirations than generally believed. Second, random noise-like aspirations may be difficult to separate from background noise via accelerometry alone, without corroborating evidence, such as videofluoroscopy. However, we note that the stationarity test statistic value itself can be viewed as an extracted signal feature. Given the continuum of values obtained, the stationarity statistic may serve as a useful feature for categorizing different aspiration signals, and in combination with other features may facilitate automatic detection. In fact, our current research suggests that a stationarity feature along with other statistical signal features may indeed be useful in the discrimination of aspirations from other swallow events, such as healthy swallows. Further investigation of these differences would be the next logical step for future studies.

V. Conclusion

A. Limitations

The median frequency as a single location estimator may not adequately represent the spectral density structure. Ideally, we would like to compare the entire density function across time. Possible future routes might be to parametrically estimate the density function and compare the evolution of the model parameters. Although crude, the median frequency does give a rough sense of the temporal variation of the frequency spectrum.

Strictly speaking, the reverse arrangements test only detects nonstationarity due to time-varying mean or variance and not due to dynamic frequency content. However, in the aspiration signals observed, changes in frequency seldom occur in isolation. We can thus argue that for the most part, the reverse arrangements test does capture nonstationarity due to time-evolving frequency content, albeit in combination with time-varying variance.

The findings are based on paediatric aspiration signals. With the maturation or degeneration of protective reflexes and physiological structures involved in swallowing [47], [48], the temporal characteristics of aspirations may change as well. Further study is thus required to determine the generalizability of the present results to the adult and geriatric populations.

B. Summary

We have investigated the stationarity of a large sample of paediatric aspiration signals. Methodologically, we find that window sizes of 5 ms in duration are justified and that the choice of signal trimming does not impact stationarity testing. Forty-five percent of the tested aspiration signals are nonstationary, with time-varying frequency and variance as the predominant sources of nonstationarity. The results of stationarity testing seem to agree with clinical observations but suggest that a greater variety of aspiration signals exist than previously identified. This latter finding poses significant challenges to aspiration detection by accelerometry alone.

Acknowledgment

The authors are grateful for the tremendous efforts of M. Cheung, S. Redekop, and H. Schwellnus (data collection); J. Chan and Dr. D. Alton (radiology); and J. Wadds (swallowing clinic). The constructive comments made by the various anonymous reviewers are also much appreciated.

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Excitability of Chronic Hemiparetic Muscles: Determination of Chronaxie Values and Strength-Duration Curves and Its Implication in Functional Electrical Stimulation

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***Abstract*—Central nervous system disorders affect the anatomy and physiology of the lower motoneuron. This fact has an impact on the stimulation parameters, especially on the duration of the stimulating impulses, for functional electrical stimulation in chronic hemiparetic patients.**

The aim of this study was thus to test the excitability and to determine chronaxie values and strength-duration curves of weak wrist and finger extensor muscles and spastic finger and wrist flexor muscles in the hemiparetic arm.

Twelve patients with chronic hemiplegia (>6 months after the onset of the cerebral lesion) participated in the study. A constant current stimulator was used. As to chronaxie values no significant differences were found between the extensor muscles (mean $\pm$ SD: 0.44 $\pm$ 0.16 ms) and flexor muscles (mean $\pm$ SD: 0.36 $\pm$ 0.22 ms). A moderate variability was seen for both extensor muscles (0.2–0.8 ms) and flexor muscles (0.1–0.9 ms). These values are well within the normal range determined for innervated muscles. All strength-duration curves were completely normal for each muscle.

We conclude that in chronic hemiparetic muscles, impulses of the same duration can be used as in muscles of healthy subjects.

***Index Terms*—Chronaxie, functional electrical stimulation, hemiplegia, strength-duration curves.**

I. Introduction

The use of electrical stimulation to improve the functional abilities in patients with neuromuscular system impairment is called functional electrical stimulation (FES). The FES in the upper extremities of chronic hemiplegic patients is an area of increasing interest. Literature supports its effect in reducing the muscle tone, increasing the strength, reducing contractures, and, as a consequence, improving the function of the treated arm [1]–[8]. A common problem after a cerebral hemispheric lesion is spasticity of the wrist and finger flexors and a weakness or paralysis of the wrist and finger extensors. Mostly, the weak finger and wrist extensor muscles are stimulated by FES [1]–[8]. Sometimes a reciprocal stimulation of the weak extensor muscles and spastic flexor muscles is performed [4], [5].

Hemiparesis after upper motoneuron lesions leads to atrophy and abnormal metabolic function of the muscles of the affected side resulting from disuse and altered central neural innervation [9]–[12]. Several articles imply that central nervous system disorders affect the anatomy and physiology of the lower motoneuron [13]–[16]. This fact has an impact on the stimulation parameters of FES in chronic hemiparetic patients. The current induced in biological tissues must be of sufficient amplitude and duration to bring excitable cells to a critical transmembrane voltage, called threshold, in order to evoke an action potential. To describe the stimulus characteristics for activation of excitable tissue chronaxie values and strength-duration curves are used [17]–[22]. Chronaxie is the minimum duration of a rectangular current

Manuscript received July 1, 2004; revised October 1, 2004, December 10, 2004; accepted December 15, 2004.

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Digital Object Identifier 10.1109/TNSRE.2005.843439