Computers in Biology and Medicine 40 (2010) 839–844

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Understanding the statistical persistence of dual-axis swallowing accelerometry signals

Ervin Sejdić [a,b,*], Catriona M. Steele [c], Tom Chau [a]

[a] Bloorview Research Institute, Bloorview Kids Rehab and the Institute of Biomaterials and Biomedical Engineering, University of Toronto, Toronto, Ontario, Canada
[b] Division of Gerontology, Beth Israel Deaconess Medical Center and Harvard Medical School, Harvard University, Boston, MA, USA
[c] Toronto Rehabilitation Institute and the Department of Speech-Language Pathology, University of Toronto, Toronto, Ontario, Canada

ARTICLE INFO

Article history:
Received 28 April 2010
Accepted 14 September 2010

Keywords:
Dual-axis swallowing accelerometry signals
Detrended fluctuation analysis

ABSTRACT

Swallowing accelerometry is a biomechanical approach for the assessment of difficulties during deglutition. However, the effects of various swallowing tasks and different anthropometric/demographic variables on the statistical behavior of these accelerometric signals are unknown. In particular, to understand the statistical persistence of these signals, we used detrended fluctuation analysis (DFA) to analyze accelerometric data collected from 408 healthy participants during dry, wet and wet chin tuck swallowing tasks. The results of DFA were then examined for potential influences of age, gender or body mass index. Several important conclusions were reached. First, the strongest persistence was observed for the wet chin tuck swallows. Second, the vibrations in the superior–inferior (S–I) direction generally have stronger temporal dependencies than those in the anterior–posterior (A–P) direction. Both of these phenomena can be attributed to the dominating influence of head movements on the amplitude of vibrations in the S–I direction. Third, gender, age and body mass index of the participants did not impact the observed persistence for dry and wet chin tuck swallows, while a gender effect was identified for wet swallows. In particular, male participants experienced more Brownian-like statistical dependencies in their swallowing signals. Future developments in the field should attempt to remove signal components associated with strong statistical persistence, as they tend to be associated with non-swallowing phenomena.

1. Introduction

Swallowing accelerometry is a technique involving the attachment of an accelerometer at the patient's neck. The technique has emerged as an alternative investigational approach for non-invasive assessment of swallowing disorders [1,2]. Even though single-axis accelerometers were initially used [3–6], it has been shown recently that dual-axis accelerometers yield more information and enhance diagnostic capabilities [7–9]. The advantage of dual-axis swallowing accelerometry is that it reflects the two-dimensional movement of the hyoid and the larynx during swallowing [10].

Non-swallowing related phenomena, including small low-frequency vibrations observed in the baseline state (e.g., [9]) or head motions during swallowing (e.g., [7,8]), can alter the amplitude of swallowing accelerometry signals. A recent contribution showed that the small vibrations present in baseline dual-axis accelerometry signals (without swallows) and various head motions introduce strong correlations in these signals [11]. Furthermore, the A–P axis experienced stronger statistical persistence in comparison to the S–I axis [11]. However, several open questions exist about the nature of these observed dependencies when swallows are actually present in the signals. First, it is unknown how the presence of swallows will alter the observed baseline statistical persistence, i.e., whether the dependencies become stronger or weaker. Second, given that various maneuvers (e.g., chin tuck) are used in practice to ensure safe deglutition, their potential influence on the observed baseline statistical persistence is also of interest. Third, it is unknown whether any demographic/anthropometric variables such as age, gender or body mass index impact statistical persistence, since in the previous contributions it has been shown that these variables impact swallowing (e.g., [7]). The analysis conducted in this paper answers these open questions about statistical persistence in dual-axis swallowing accelerometry signals. These answers will help us to understand whether or not it is necessary to remove signal components associated with long-range dependencies (if possible) in swallowing accelerometry for clinical decision support.

The main contribution of this paper is the characterization of statistical persistence in dual-axis swallowing accelerometry signals. Previous research has only unveiled scaling characteristics of baseline cervical accelerometry in the absence of swallowing. In the following sections we describe the data collection and analysis used to probe the effects of swallowing,

* Corresponding author at: Division of Gerontology, Beth Israel Deaconess Medical Center and Harvard Medical School, Harvard University, Boston, MA, USA.
E-mail addresses: esejdic@ieee.org (E. Sejdić), steele.catriona@torontorehab.on.ca (C.M. Steele), tom.chau@utoronto.ca (T. Chau).

0010-4825/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.compbiomed.2010.09.002

the chin tuck maneuver, gender and age on the statistical persistence of dual-axis cervical accelerometry signals.

2. Methodology

2.1. Detrended fluctuation analysis

From previous studies, it is known that dual-axis swallowing accelerometry signals are non-stationary [8]. Detrended fluctuation analysis (DFA) is a scaling analysis method that estimates an exponent α indicative of the (auto-)correlation properties of a non-stationary time series [12,13]. DFA facilitates detection of long-range behavior embedded in non-stationary time series while avoiding spurious long-range correlations that may be artifacts of non-stationary trends [14,15].

In short, DFA evaluates deviations of signal segments around local trends through a series of steps as shown in Fig. 1. For full details, the reader is referred to previous contributions (e.g., [12–15]). From the nature of the algorithm, an increasing length of a segment produces an increasing value of the fluctuation function since longer segments can introduce greater deviations from a local trend. Therefore, these fluctuations are modeled as having a power-law behavior with respect to the segment length, while being independent of external trends and signal amplitude:

$$F(M) \propto M^{\alpha} \tag{1}$$

where $F(M)$ represents the fluctuation function, and M represents the segment length. In other words, α is the slope of the line observed in the log–log representation of $F(M)$ as a function of M. In general, α can be related to correlation properties of a time series and its power spectral density [12,16,17]. Additionally, α is also related to the Hurst exponent such that $\alpha = H$ for $0 < H < 1$ and $\alpha = H + 1$ for $H > 1$ [18–20]. From a physical point of view, α denotes the "roughness" of a time series with higher values of α denoting smoother time series. For example, white Gaussian noise is considered very rough and its $\alpha = 0.5$, while $\alpha = 1.5$ for the Brownian motion, which is considered very smooth [21].

2.2. Data collection

In this paper, we analyzed the data collected in [7,22–24] under the study protocol that was approved by the research ethics boards of the Toronto Rehabilitation Institute and Holland Bloorview Kids Rehabilitation Hospital, both located in Toronto, Ontario, Canada. In brief, 408 healthy adult participants (aged 18–65) with no known swallowing disorders were recruited and all provided written consent. In order to acquire swallowing accelerometry signals, a dual-axis accelerometer (ADXL322, Analog Devices) was placed on the neck of each participant anterior to the cricoid cartilage and secured with double-sided tape. The two axes were positioned in the anterior–posterior (A–P) and superior–inferior (S–I) directions. The accelerometer has a measurement range of ± 5 g, a bandwidth of 2.5 kHz, a resonant frequency of 5.5 kHz, and a sensitivity of 174 mV/g. A power supply (Model 1504, BK Precision) set at 5 V was used to power the accelerometer. During the data collection, participants completed three types of swallows: five saliva swallows, five water swallows by cup with their chin in the natural position (i.e., perpendicular to the ear) and five water swallows in the chin-tucked position. The entire data collection session lasted 15 min per participant.

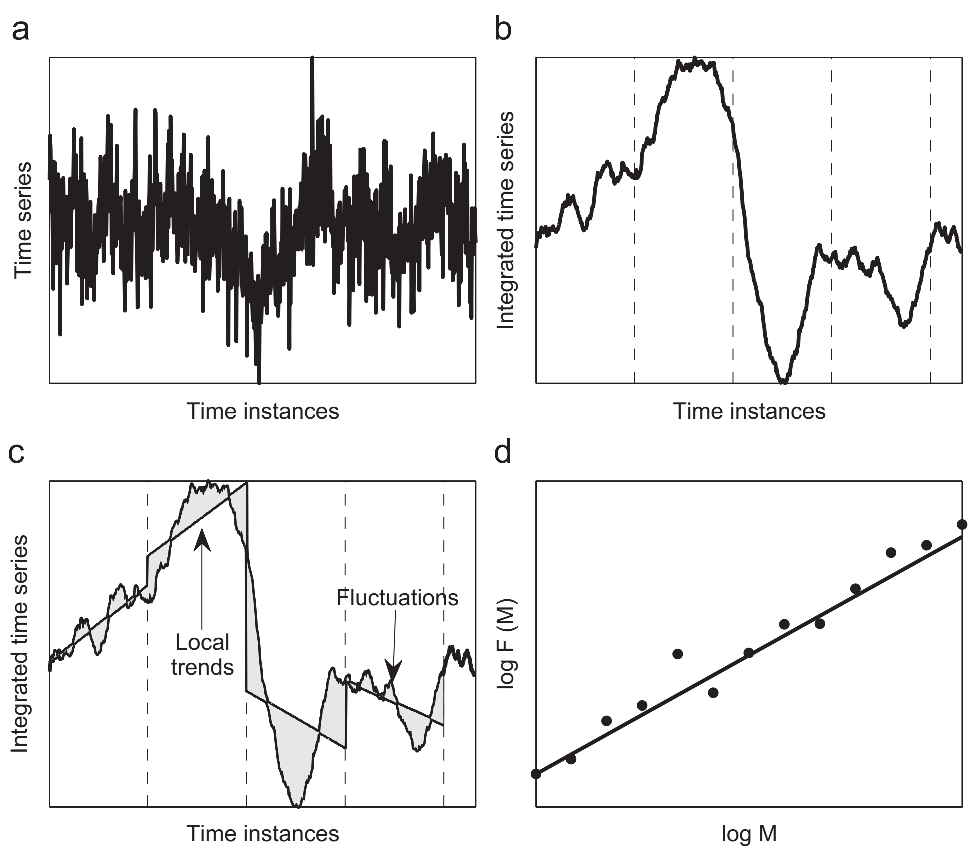

Fig. 1. DFA steps: (a) We begin with a raw time series. (b) Secondly, we evaluate the cumulative sum of the series and divide into non-overlapping segments of equal length. (c) Thirdly, a local trend for each of the segments is calculated by a least-square fit of the data. Then, the trend is removed and the variance around each trend is determined. (d) As the last step, the variance for all segments is averaged and its square root function yields the fluctuation at segment length M. The estimated scaling exponent, α, is the slope of the least squares fitted line.

2.3. Data analysis

DFA was carried out to examine statistical persistence in the A–P and S–I directions for the dual-axis swallowing accelerometry signals. The value of M in DFA was chosen from the predetermined set $\mathcal{M}$ defined as in [11]

$$\mathcal{M} = \{M : M \in \mathbb{N} \text{ and } \lfloor N/100 \rfloor \leq M \leq \lfloor N/10 \rfloor\} \tag{2}$$

where the set contains 50 points equally spaced on a logarithmic scale. These values were chosen based on previous contributions showing that very large M are preferred in order to deal with possibly very long correlations [13]. However, as M approaches N the error in the estimation of α increases significantly [25]. In fact, the error associated with the estimation of α is inversely proportional to the square root of the ratio M/N [13]. Similarly, it has been suggested that the minimal value of M should be chosen such that Markovian correlations do not affect the estimation of α [13]. Therefore, we used $N/100$ and $N/10$ for the minimal and maximal values of M, respectively, since they provided satisfactory results and the set $\mathcal{M}$ provided us with a sufficient number of points to carry out an accurate fitting of a local trend [11]. A first order polynomial was used for detrending the signals considered in this paper, given that higher order polynomials tend to overfit the local trend of dual-axis swallowing accelerometry signals [11]. Lastly, we investigated possible demographic effects on those correlations using the Mann–Whitney test [26]. In this paper, a 5% statistical significance level was used.

It should be also pointed out that there were pre-processing steps involved in the analysis. The acquired signals were pre-processed with the inverse filters developed in [9]. Such filtered signals were then denoised using the wavelet based approach [23,27]. Specifically, we implemented a 10-level discrete wavelet transform using the discrete Meyer wavelet with soft thresholding as in a previously reported analysis of baseline accelerometry signals [9].

3. Results and discussion

The results of DFA of dual-axis swallowing accelerometry signals are summarized in Tables 1–5. By comparing the overall α values for the three swallowing types, it can be observed that the largest α values occur during the wet chin tuck swallows, while the smallest values occur for the dry swallows. This observation holds in the A–P direction regardless of the gender, age or BMI of participants. On the other hand, the α values for the three swallowing types were statistically different in both directions ($p \ll 0.01$).

Higher α values were observed in the S–I direction than in the A–P direction. These results are expected based on the previous contributions (e.g., [7,8]), which also noticed that head movements have more dramatic effects on the vibrations in the S–I rather than A–P direction (refer to Fig. 2 for three sample swallows from a participant). In addition, the highest α values are observed for wet chin tuck swallows. This observation can be explained by the fact that during wet chin tuck swallows, participants were asked to make repetitive head movements. These movements induced stronger temporal dependencies in the swallowing accelerometry signals.

Visually inspecting the sample signals in Fig. 2(a), (c) and (e), one might expect $0 < \alpha < 0.5$, given that segments with small fluctuations (i.e., baseline) are intermingled with segments possessing larger fluctuations (i.e., swallows). Nevertheless, the analyzed dual-axis swallowing accelerometry signals exhibited strong positive correlations. We thus speculate that the underlying baseline characteristics (e.g., weak vibrations caused by vasomotion [9]) and head motions are largely responsible for the observed statistical persistence. This would imply that these temporal dependencies ought to be carefully considered in the development of accelerometry-based decision support tools.

When comparing the α values presented here with those reported in [11], we observe a weaker statistical dependence in the A–P direction than in the S–I direction when swallows are present in the recordings. This is due to the fact that head motions

Table 1
α values grouped by gender.

	Overall		Male		Female	
	A–P	S–I	A–P	S–I	A–P	S–I
Dry swallows	0.88 ± 0.23	1.09 ± 0.15	0.89 ± 0.22	1.08 ± 0.15	0.87 ± 0.24	1.10 ± 0.16
Wet swallows	0.97 ± 0.23	1.14 ± 0.16	1.02 ± 0.24	1.15 ± 0.17	0.92 ± 0.22	1.12 ± 0.16
Wet chin tuck	1.26 ± 0.23	1.42 ± 0.17	1.28 ± 0.23	1.41 ± 0.17	1.25 ± 0.22	1.43 ± 0.17

Table 2
α values in the A–P direction arranged by participant age.

	$18 \leq$ Age < 35	$35 \leq$ Age < 45	$45 \leq$ Age < 55	$55 \leq$ Age < 65
Dry swallows	0.90 ± 0.24	0.86 ± 0.22	0.88 ± 0.23	0.87 ± 0.21
Wet swallows	0.98 ± 0.25	0.95 ± 0.23	0.96 ± 0.22	0.98 ± 0.22
Wet chin tuck	1.25 ± 0.23	1.27 ± 0.24	1.24 ± 0.22	1.30 ± 0.22

Table 3
α values in the S–I direction arranged by participant age.

	$18 \leq$ Age < 35	$35 \leq$ Age < 45	$45 \leq$ Age < 55	$55 \leq$ Age < 65
Dry swallows	1.10 ± 0.15	1.09 ± 0.15	1.08 ± 0.16	1.08 ± 0.16
Wet swallows	1.13 ± 0.18	1.15 ± 0.15	1.14 ± 0.15	1.14 ± 0.15
Wet chin tuck	1.40 ± 0.17	1.42 ± 0.18	1.46 ± 0.18	1.42 ± 0.15

Table 4
α values in the A–P direction arranged by BMI.

	BMI < 18.5	$18.5 \leq$ BMI < 25	$25 \leq$ BMI < 30	BMI ≥ 30
Dry swallows	0.87 ± 0.20	0.89 ± 0.24	0.91 ± 0.21	0.84 ± 0.22
Wet swallows	0.95 ± 0.27	0.98 ± 0.25	0.96 ± 0.22	0.97 ± 0.21
Wet chin tuck	1.22 ± 0.27	1.27 ± 0.24	1.26 ± 0.21	1.25 ± 0.22

Table 5
α values in the S–I direction arranged by BMI.

	BMI < 18.5	$18.5 \leq$ BMI < 25	$25 \leq$ BMI < 30	BMI ≥ 30
Dry swallows	1.09 ± 0.13	1.09 ± 0.16	1.10 ± 0.15	1.07 ± 0.15
Wet swallows	1.15 ± 0.15	1.13 ± 0.16	1.13 ± 0.16	1.14 ± 0.17
Wet chin tuck	1.40 ± 0.17	1.42 ± 0.16	1.41 ± 0.15	1.43 ± 0.19

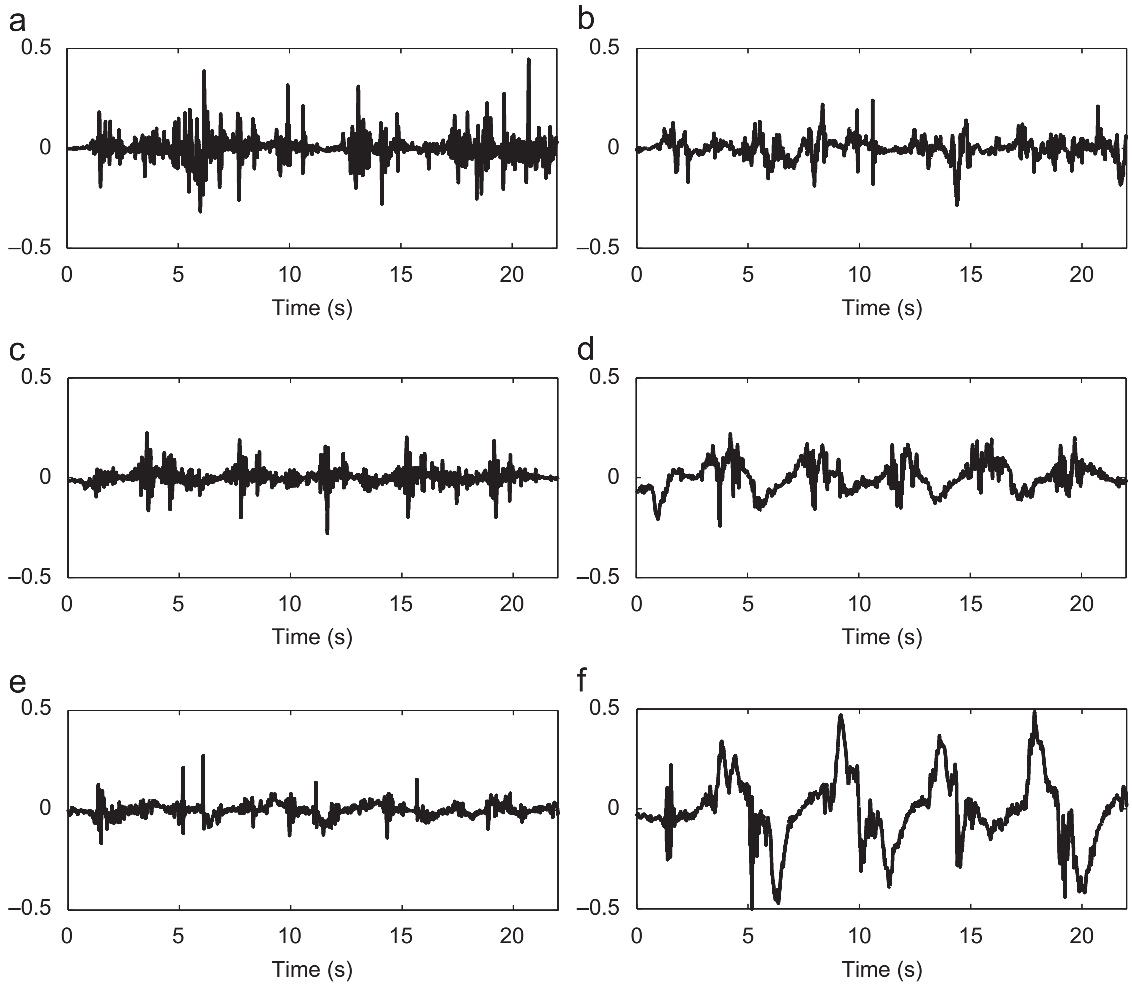

Fig. 2. Sample swallows from a participant: sample dry swallowing accelerometry signals in the A–P direction (a) and the S–I direction (b); sample wet swallowing accelerometry signals in the A–P direction (c) and the S–I direction (d); sample wet chin tuck swallowing accelerometry signals in the A–P direction (e) and the S–I direction (f).

exert stronger effects on the signal amplitude in the S–I direction than in the A-P direction (e.g., [7,8]). Also, the reason for weaker dependencies in the A–P direction is that swallows produce more prominent, but transient signal deflection in the A–P measurement. As expected, the presence of vibrations which do not persist for a complete observation period diminishes long-range dependencies. Nevertheless, a decay in α was not observed in the S–I direction, since head motions induce stronger amplitude alterations in the S–I signal, and hence higher correlations in the time series [28]. The prevailing effects of head motions in the S–I direction thus yielded a higher value for α. The scaling exponent, α, can be interpreted as the "roughness" of a time series [21]. This interpretation helps us to appreciate the occurrence of Brownian-like statistical persistence in the S–I direction. Head motions, especially during chin tuck swallows, make these signals appear very smooth in comparison to the signals from the A–P direction.

There were no gender effects on dry and wet chin tuck swallows in both directions ($p > 0.16$). However, we observed gender-based statistical differences for wet swallows in both directions ($p < 0.01$). Given that head motions are responsible for the observed statistical persistence, we anticipate that even minimal motions during wet swallows induced the observed differences. Furthermore, these results coincide with findings presented in [22], which demonstrated that there are statistically significant gender-based differences in neck angles during wet swallows.

Next, we considered the effects of age on α values. A linear regression analysis showed that α values from both directions for the three swallowing types are not affected by the increasing age of participants ($p > 0.15$). This is an interesting finding given that a typical swallowing signal contains multiple swallows, baseline vibrations and possible vibrations associated with head movements. All these components of dual-axis swallowing accelerometry signals are affected by the age of the participant. As reported previously, the baseline vibrations are related to the cardiovascular dynamics of the participant (e.g., [7,9,11]) and cardiac dynamics slow down with age (e.g., [29,30]), i.e., slower variations induce longer dependencies. Also, older participants require a longer time period to complete a swallow due to the age-related decoupling of oral and pharyngeal stages of swallowing [31]. Nevertheless, none of these factors increased α values in older participants, most likely, due to the prevailing effects of head motions.

Another important aspect of this research was to understand whether or not an increasing level of adipose tissue had an effect on swallowing accelerometry. Here, in particular, we investigated the potential effect of BMI on the statistical persistence in dual-axis swallowing accelerometry signals. Tables 4 and 5 summarize the results of such an analysis, and α values are grouped according to standardized BMI intervals [32]. These results clearly show that BMI did not affect the α values in either direction, i.e., the statistical persistence in dual-axis swallowing accelerometry signals remains unchanged for increasing BMI (linear regression analysis: $p > 0.17$). Previous reports in the field found that an increased level of adipose tissue increases the duration of a swallow accelerometry signal [7]. However, our findings suggest that changes in swallow signal duration have minimal effects on statistical persistence in comparison to baseline effects (e.g., [11]). Specifically, these results show that head movements have dominant effects on the observed statistical persistence, since the strongest persistence was observed in the S–I direction for wet chin tuck swallows.

3.1. Implications

The key finding is that wet chin tuck swallows induce the greatest statistical persistence among the types of swallows studied and that this effect is most prominent in the S–I direction and tends to mask any other previously reported effect on statistical persistence (e.g., age). This finding bears several important implications on the design and usage of any medical device exploiting dual-axis swallowing accelerometry. Ideally, the device ought to have the capability to remove large magnitude, low frequency trends due to head motion. The clinical protocol associated with the device should probably avoid or limit swallowing maneuvers which mandate head motions. Alternatively, the measurement of swallowing vibrations may require immobilization of the patient's head. In light of the present findings, swallowing accelerometry might not be appropriate for individuals with Parkinsonian, essential, dystonic or other types of head tremors.

Head motions introduce low-frequency trend-like components into dual-axis swallowing accelerometry signals. Therefore, methods for detrending non-stationary biomedical data (e.g., [33]) may be suitable for removing these low frequency components.

4. Conclusion

In this paper, the statistical persistence of dual-axis swallowing accelerometry signals has been examined. Wet chin tuck swallows consistently experienced the strongest statistical dependencies amongst the considered swallows, due to the dominant effect of head motion. Stronger dependencies were found in the S–I direction than in the A–P direction regardless of the swallow type. Finally, there were no effects of gender, age or BMI on statistical persistence, except for the gender effect observed for wet swallows.

Conflict of interest statement

None declared.

Acknowledgments

This research was funded in part by the Ontario Centres of Excellence, the Toronto Rehabilitation Institute, Bloorview Kids Rehab, and the Canada Research Chairs Program.

References

[1] N.P. Reddy, B.R. Costarella, R.C. Grotz, E.P. Canilang, Biomechanical measurements to characterize the oral phase of dysphagia, IEEE Transactions on Biomedical Engineering 37 (4) (1990) 392–397.
[2] N.P. Reddy, E.P. Canilang, J. Casterline, M.B. Rane, A.M. Joshi, R. Thomas, R. Candadai, Noninvasive accelaration measurements to characterize the pharyngeal phase of swallowing, Journal of Biomedical Engineering 13 (September) (1991) 379–383.
[3] J. Lee, S. Blain, M. Casas, D. Kenny, G. Berall, T. Chau, A radial basis classifier for the automatic detection of aspiration in children with dysphagia, Journal of NeuroEngineering and Rehabilitation 3 (14) (2006) 17.
[4] T. Chau, D. Chau, M. Casas, G. Berall, D.J. Kenny, Investigating the stationarity of paediatric aspiration signals, IEEE Transactions on Neural Systems and Rehabilitation Engineering 13 (1) (2005) 99–105.
[5] A. Das, N.P. Reddy, J. Narayanan, Hybrid fuzzy logic committee neural networks for recognition of swallow acceleration signals, Computer Methods and Programs in Biomedicine 64 (2) (2001) 87–99.
[6] N.P. Reddy, A. Katakam, V. Gupta, R. Unnikrishnan, J. Narayanan, E.P. Canilang, Measurements of acceleration during videofluorographic evaluation of dysphagic patients, Medical Engineering and Physics 22 (6) (2000) 405–412.
[7] E. Sejdić, C.M. Steele, T. Chau, Segmentation of dual-axis swallowing accelerometry signals in healthy subjects with analysis of anthropometric effects on duration of swallowing activities, IEEE Transactions on Biomedical Engineering 56 (4) (2009) 1090–1097.
[8] J. Lee, C.M. Steele, T. Chau, Time and time–frequency characterization of dual-axis swallowing accelerometry signals, Physiological Measurement 29 (9) (2008) 1105–1120.
[9] E. Sejdić, V. Komisar, C.M. Steele, T. Chau, Baseline characteristics of dual-axis swallowing accelerometry signals, Annals of Biomedical Engineering 38 (3) (2010) 1048–1059.
[10] D. Zoratto, T. Chau, C.M. Steele, Hyolaryngeal excursion as the physiological source of swallowing accelerometry signals, Physiological Measurement 31 (6) (2010) 843–855.
[11] E. Sejdić, C.M. Steele, T. Chau, Scaling analysis of baseline dual-axis cervical accelerometry signals, Computer Methods and Programs in Biomedicine, in press, doi:10.1016/j.cmpb.2010.06.010.
[12] C.-K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Mosaic organization of DNA nucleotides, Physical Review E 49 (2) (1994) 1685–1689.
[13] S.M. Ossadnik, S.V. Buldyrev, A.L. Goldberger, S. Havlin, R.N. Mantegna, C.-K. Peng, M. Simons, H.E. Stanley, Correlation approach to identify coding regions in DNA sequences, Biophysical Journal 67 (1) (1994) 64–70.
[14] Z. Chen, P.C. Ivanov, K. Hu, H.E. Stanley, Effect of nonstationarities on detrended fluctuation analysis, Physical Review E 65 (4) (2002) 041107.
[15] M. Jospin, P. Caminal, E.W. Jensen, H. Litvan, M. Vallverdu, M.M.R.F. Struys, H.E.M. Vereecke, D.T. Kaplan, Detrended fluctuation analysis of EEG as a measure of depth of anesthesia, IEEE Transactions on Biomedical Engineering 54 (5) (2007) 840–846.
[16] J.W. Kantelhardt, E. Koscielny-Bunde, H.H.A. Rego, S. Havlin, A. Bunde, Detecting long-range correlations with detrended fluctuation analysis, Physica A: Statistical Mechanics and its Applications 295 (3–4) (2001) 441–454.
[17] T. Penzel, J.W. Kantelhardt, L. Grote, J.H. Peter, A. Bunde, Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea, IEEE Transactions on Biomedical Engineering 50 (10) (2003) 1143–1151.
[18] D. Delignieres, S. Ramdani, L. Lemoine, K. Torre, M. Fortes, G. Ninot, Fractal analyses for short time series: a re-assessment of classical methods, Journal of Mathematical Psychology 50 (6) (2006) 525–544.
[19] F. Esen, H. Esen, Detrended fluctuation analysis of laser Doppler flowmetry time series: the effect of extrinsic and intrinsic factors on the fractal scaling of microvascular blood flow, Physiological Measurement 27 (11) (2006) 1241–1253.
[20] A. Eke, P. Herman, L. Kocsis, L.R. Kozak, Fractal characterization of complexity in temporal physiological signals, Physiological Measurement 23 (1) (2002) R1–R38.
[21] C.-K. Peng, S. Havlin, H.E. Stanley, A.L. Goldberger, Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series, Chaos: An Interdisciplinary Journal of Nonlinear Science 5 (1) (1995) 82–87.
[22] D. Hung, E. Sejdić, C.M. Steele, T. Chau, Extraction of average neck flexion angle during swallowing in neutral and chin-tuck positions, BioMedical Engineering OnLine 8 (1) (2009) 25-1-9.
[23] E. Sejdić, C.M. Steele, T. Chau, A procedure for denoising dual-axis swallowing accelerometry signals, Physiological Measurement 31 (1) (2010) N1–N9.
[24] E. Sejdić, T.H. Falk, C.M. Steele, T. Chau, Vocalization removal for improved automatic segmentation of dual-axis swallowing accelerometry signals, Medical Engineering and Physics 32 (6) (2010) 668–672.
[25] S. Damouras, M.D. Chang, E. Sejdić, T. Chau, An empirical examination of detrended fluctuation analysis for gait data, Gait and Posture 31 (3) (2010) 336–340.
[26] H.B. Mann, D.R. Whitney, On a test of whether one of two random variables is stochastically larger than the other, The Annals of Mathematical Statistics 18 (1) (1947) 50–60.
[27] D.L. Donoho, De-noising by soft-thresholding, IEEE Transactions on Information Theory 41 (3) (1995) 613–627.
[28] R. Karasik, N. Sapir, Y. Ashkenazy, P.C. Ivanov, I. Dvir, P. Lavie, S. Havlin, Correlation differences in heartbeat fluctuations during rest and exercise, Physical Review E 66 (6) (2002) 062902-1–062902-4.
[29] M. Brandfonbrener, M. Landowne, N.W. Shock, Changes in cardiac output with age, Circulation 12 (4) (1955) 557–566.

[30] I.A. O'Brien, P. O'Hare, R.J. Corrall, Heart rate variability in healthy subjects: effect of age and the derivation of normal ranges for tests of autonomic function, British Heart Journal 55 (4) (1986) 348–354.
[31] J.F. Tracy, J.A. Logemann, P.J. Kahrilas, P. Jacob, M. Kobara, C. Krugler, Preliminary observations on the effects of age on oropharyngeal deglutition, Dysphagia 4 (2) (1989) 90–94.
[32] Global database on body mass index, World Health Organization, August 25, 2010 [Online], Available: ⟨http://www.who.int/bmi/index.jsp⟩.
[33] H. Liang, Q.-H. Lin, J.D.Z. Chen, Application of the empirical mode decomposition to the analysis of esophageal manometric data in gastro-esophageal reflux disease, IEEE Transactions on Biomedical Engineering 52 (10) (2005) 1692–1701.