35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Wearable Diet Monitoring Through Breathing Signal Analysis

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Abstract **- This paper presents the design, system structure and performance for a wireless and wearable diet monitoring system. Food and drink intake can be detected by the way of detecting a person's swallow events. The system works based on the key observation that a person's otherwise continuous breathing process is interrupted by a short apnea when she or he swallows as a part of solid or liquid intake process. We detect the swallows through the difference between normal breathing cycle and breathing cycle with swallows using a wearable chest-belt. Three popular machine learning algorithms have been applied on extracted time and frequency domain features. It is shown that high detection performance can be achieved with only few features.**

Keywords **– Wearable Sensors; Swallow Detection; Food Intake Monitoring; Breathing Pattern Analysis; Classifiers**

I. INTRODUCTION

According to the data from World Health Organization, worldwide obesity increased over 200% since 1980 [1]. It has been proven that obesity can cause coronary heart disease, type-2 diabetes, and various types of cancers [2]. Diet control and physical exercise are the two most important components of obesity control. Traditionally, self-reported questionnaires were widely used by researchers for estimating both food intake and physical activity levels for high-risk individuals. In recent years, however, accelerometers, gyroscope, pressure sensor have been deployed for physical activity detection with high detection accuracy [3]. On the other hand, not many efforts in wearable diet monitoring are reported in the literature. An instrumented system can reduce the subjectivity [4] associated with questionnaire based self-reporting systems.

An instrumented system can detect each instance of food/drink intake, and can have enormous significance for obesity control and health monitoring. Together with self-reporting at the high level of overall dietary habits, the system can transform the obesity and health management practices by quantifying calorie intake estimates and trends for its users.

Swallow detection and analysis methods are generally divided into two categories, invasive and noninvasive. An invasive method for swallow detection is Videofluoroscopy which uses X-ray to monitor swallowing process in order to evaluate patients with neurological conditions affecting swallowing [5]. While providing ample information about different aspects of the swallow process, these methods are too involved and cannot be used for everyday monitoring and food/drink intake analysis purposes. Non-invasive methods use biological signals such as electromyography, sound, and movement to detect swallows. Surface electromyography (SEMG) and sound signal are used to detect the activation of muscles and the sound associated with swallow events [6]. The SEMG electrodes are normally attached to the bare skin in the neck region, which may raise user acceptability issues for prolonged usage due to cosmetic and safety reasons. A two-microphone system is developed in [7] for recording chewing and swallowing sound through the ear canal as well as externally through the air. Placing such microphones has similar cosmetic issues and therefore its suitability for prolonged usage is questionable. Respiratory Inductance Plethysmography (RIP) is used for swallow detection by measuring the airflow [8] in trachea. The RIP belts used for this method are often too involving to be useable for prolonged use in daily life settings.

We present a wearable sensor system for swallow monitoring in this paper. The system works based on the key observation that during swallowing, because the trachea is blocked, a person is not able to breathe, causing a temporary *apnea*. Using a wearable chest-belt, we detect swallows by the way of detecting apneas extracted from breathing signal captured by the chest-belt. Since the belt can be worn inside, outside, or between garments (it does not need skin contact), it has the potential for prolonged comfortable daily usage without raising any cosmetic issues. After the swallow sequence is recorded, swallow pattern analysis can potentially be used for identifying non-intake swallows (or empty swallows), solid intake swallows, and drinking swallows.

In our previous work [9], we reported a similar system with algorithms designed specifically for liquid intake monitoring. In this paper, we present hardware, algorithm, and software extension of the same concept for monitoring both liquid and solid intakes.

II. SYSTEM COMPONENTS

As shown in Fig. 1, an embedded wearable sensor system is worn on the chest for collecting the breathing signal and transmitting it to a smart phone through Bluetooth. The embedded belt system contains: 1) a piezo-respiratory belt for converting the changes of tension during breathing to a voltage signal, 2) an amplifier and signal shaping circuit for formatting the raw voltage signal to a format compatible for an ADC chip, 3) a processor and radio subsystem (TI EZ430-RF256x), and 4) one 3.7V 300mAH polymer rechargeable battery. The entire package weighs approximately 40 grams. The 300mAh polymer battery is able to support the system for more than 30 hours of continuous operation on a single charge. After the signal is received by the smart phone, it is stored on an SD card attached to the phone. The advantage of using an embedded wireless link is that the developed swallow sensor can be networked with other physiological [10] and physical activity sensors [3] to develop a networked sensing/detection system to provide a complete instrumentation package for obesity management in the future.

This project is supported by an NIH grant R21 HL093395.

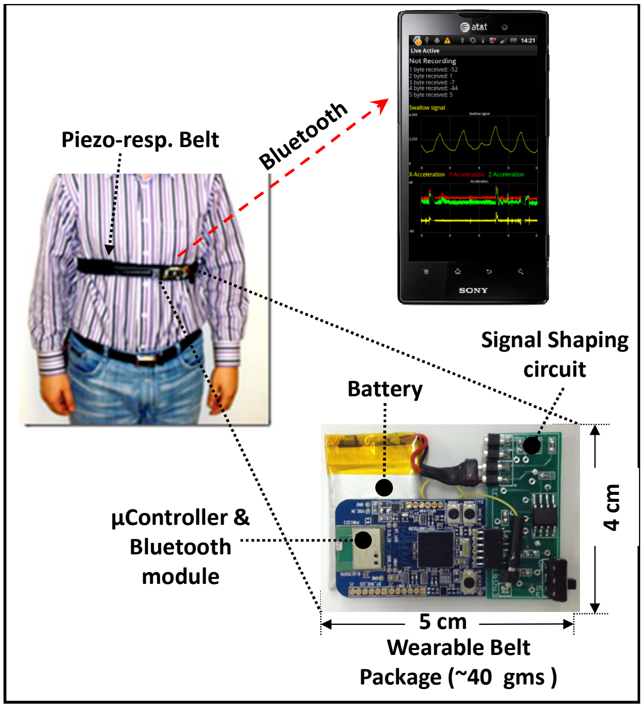

Fig. 1: Wearable wireless food intake monitoring system

III. APNEA ANALYSIS FOR SWALLOW DETECTION

Fig. 2 demonstrates a number of experimentally obtained breathing signal segments from different human subjects. The ADC readings in the figure are directly proportional to the elongation of the piezo-electric sensing belt. The rising edges correspond to inhalations and the falling edges correspond to exhalations. As shown in the figure, a breathing cycle can be either normal (i.e. *Normal Breathing Cycle* or *NBC*) or elongated due to swallow-triggered apnea. A cycle that is elongated due to an apnea at the beginning of an exhale (see Fig. 2:a for subject-1, session-1) is termed as *Breathing Cycle with Exhale Swallow* (BC-ES). For a second subject, Fig. 2:b shows swallows (i.e. apnea) during the inhale process which are termed as *Breathing Cycles with Inhale Swallow* (BC-IS).

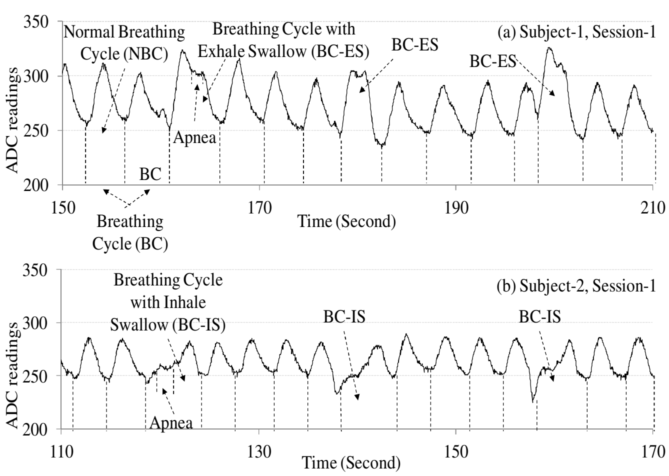

Fig. 2: Example of respiratory signal with embedded swallow signatures

Fig. 3 shows example breathing signals with *solid* and *liquid swallows*. As can be seen, for solid swallows, breathings are deeper and contain more temporal fluctuations. The key objective is to be able to classify three types of breathing cycles, namely, NBC, BC-ES, and BC-IS, and to detect if the swallow is a solid or liquid one. The challenges stem from the fact that there is significant variability in breathing waveforms across different: 1) subjects, 2) measurement instances for the same subject, and most importantly, 3) the location and duration of the apnea with respect to its breathing cycle. Among other things, this depends a great deal on the swallowing habits and the texture of the material that is being swallowed.

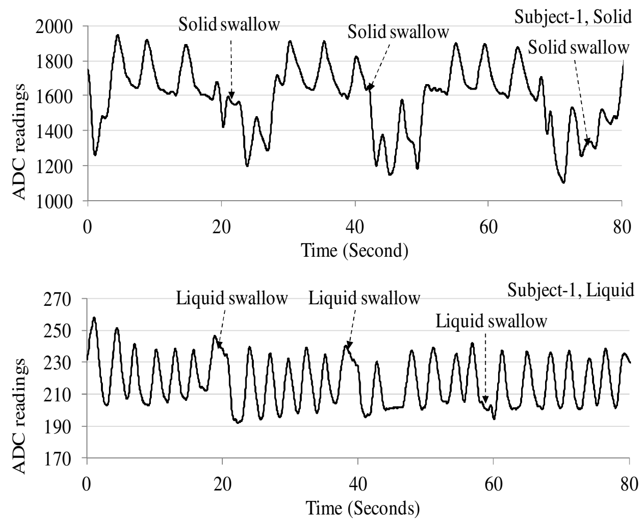

Fig. 3: Example breathing signals for solid and liquid swallows

IV. PROCESSING FOR SWALLOW DETECTION

Fig. 4 depicts the logic for classifying breathing cycles towards swallow detection. The raw data sampled by ADC at 100Hz is first fed into a low-pass filter for removing quantization noise caused by the A-to-D conversion process. Because the power spectrum of breathing signal is mainly below 2.5Hz, 100Hz is obviously sufficient. The second step is to run the filtered data stream through a peak and valley detection module in order to extract the individual breathing cycles. The next module is used for normalizing the extracted cycles in both time and amplitude dimensions. Each breathing cycle is normalized to be between 0 and 100 vertically, and interpolated to 128 sample points. Considering the average length of a breathing cycle of 3.77 seconds in our experiments, the normalized sampling rate after interpolation is mapped to 34Hz. The objective of normalization is to make sure that although different cycles may have different time and amplitude ranges (person-to-person or cycle-to-cycle for the same person), they can be effectively identified based on the apnea caused by swallowing.

The normalized breathing cycle waveforms are fed into a feature extraction module which extracts time domain or frequency domain features. These extracted features are then selected based on their discriminative power, and fed into a classifier for training or testing purposes. Number of features would affect the complexity and performance of classification. A classifier would be simple but with inferior performance if very few features are selected. Classifiers with a large number of features, however, are complex but do not necessarily provide superior performance [11].

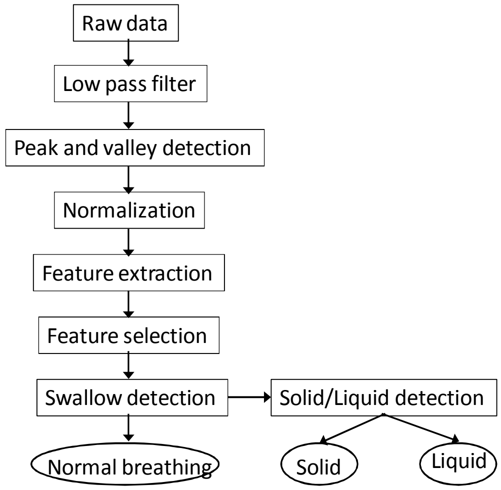

Fig. 4: Logic for swallow signature detection

A hierarchical classification scheme is used for solid and liquid swallow detection. The first classifier detects if a breathing cycle is an NBC or a breathing cycle with swallow. The second classifier detects if a swallow is a solid and liquid when the output of the first classifier is a swallow.

V. PERFORMANCE EVALUATION

Experiments using the system in Fig. 1 were carried out for swallow detection with three subjects, including 2 male and 1 female, and we are working on more subjects.

A. Experimental Methods

Each subject performed three liquid swallow sessions and three solid swallow sessions, each session lasting for five minutes. Each subject was asked to wear the instrumented chest-belt and sit still throughout the experiment. During the liquid swallow session, the subject drank water from a flask with a swallow instruction given once in every 20 seconds. 20 ml of water was added to the flask for each swallow, ensuring the swallow volume to be 20ml. Each liquid swallow session resulted in approximately 80 *Normal Breathing Cycle* (NBC) and approximately 15 breathing cycles with swallows (both *Breathing Cycle with Exhale Swallow* (BC-ES) and *Breathing Cycle with Inhale Swallow* (BC-IS)). During the solid swallow sessions, the subject was asked to eat 6 grams of crackers each time at their comfortable rate, and noted the time when he or she swallowed. Considering that the cracker would be chewed and mixed with saliva, the formed bolus was roughly the same volume as 20 ml of water swallows. The resulting swallow signals are collected over the Bluetooth channel on a smart phone as shown in Fig. 1.

B. Breathing Cycle Statistics

Table 1 summarizes the duration of different types of breathing cycles. In addition to the spread of the cycle durations across subjects, it should be observed that the cycles with swallows (i.e., both solid and liquid) are consistently longer than the normal breathing cycles. This is mainly due to the short apnea introduced by the swallow events. Moreover, it can also be observed that there is significant difference in the lengths of solid swallow and liquid swallow, which is mainly because of the different texture of the bolus in solid swallow and liquid swallow.

		NBC (Seconds)	Solid swallow (Seconds)	Liquid swallow (Seconds)
Subject 1	Maximum	5.61	6.81	7.56
	Minimum	2.36	2.91	3.36
	Average	3.24	4.86	4.79
Subject 2	Maximum	5.88	9	5.56
	Minimum	1.64	3.54	3.57
	Average	3.44	6.27	4.27
Subject 3	Maximum	4.51	9.33	6.64
	Minimum	1.93	4.26	2
	Average	3.05	6.22	4.27

Table 1: Durations of different breathing cycle types

VI. DETECTION USING MACHINE LEARNING

A. Features extraction and selection

As analyzed in our previous work [9], both time domain and frequency domain features can perform well in detecting liquid swallows. The discriminative power of those feature types, however, can be different. As shown in Fig. 5:a, for time domain features, sample points with indices near 16 and 90 are more important than other sample points in classification. As shown in Fig. 5:b, for frequency domain features, lower frequency components have more discriminative power. It was also found that the discriminative power distribution of frequency domain features are more consistent across subjects, which is why the time-domain features are used in this paper.

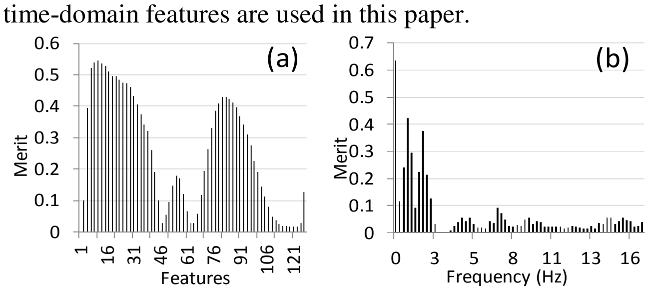

Fig. 5: Discriminative property of time and frequency domain features

The second set of classification features is derived from the first derivative of the breathing signal. As shown in Section III, it was found that the solid swallows generally create more fluctuations in the breathing signal compared to the liquid swallows. To capture such fluctuations, an additional classification feature was derived from the first derivatives of the breathing signal. More specifically, the number of ±10 crossings is used as the feature, which is defined as the number of points in the breathing signal at which the first derivative of the signal is exactly +10 or -10. Compared to the number of zero crossings, the number of ±10 crossings not only captures the fluctuations observed in solid swallows, but also helps detecting the swallows in the first place. Fig. 6 shows an example of the benefits of ±10 crossings of first derivative in detecting swallows. In this case, the number of zero crossings of first derivative is 1, which is the same as NBCs and is not sufficient in detecting the swallow, but the number of -10 crossings of the first derivative is 2 instead of 1 in case of NBC, which helps to detect the swallow.

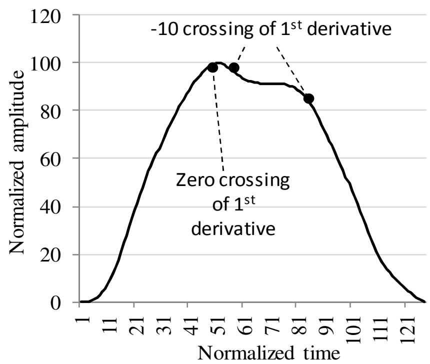

Fig. 6: Benefits of ±10 crossings as a classification feature

The third set of features is derived from various length distributions of the breathing cycles. Table 2 summarizes all the used features used in this paper.

	Features
Frequency domain features	1st order Fourier transform coefficient 2nd order Fourier transform coefficient 3rd order Fourier transform coefficient 4th order Fourier transform coefficient 5th order Fourier transform coefficient
Features from waveform	Number of +10 crossings in first derivative Number of -10 crossings in first derivative
	Breathing cycle length Inhalation length Exhalation length Inhalation depth Exhalation depth

Table 2: Features selected for classification

B. Swallow detection

All the above features are fed into the hierarchical classifier for solid and liquid swallow detection. In order to prove the generalizability, we adopt the leave-one-out method, in which case, data from all subjects are used for training except the one whose data is used for testing.

		True positive rate (%)	False positive rate (%)
Subject 1	SVM	82.9	1.6
	J48	76	2.4
	Naïve Bayes	100	1.2
Subject 2	SVM	84	0
	J48	88.6	4.9
	Naïve Bayes	97.1	4.1
Subject 3	SVM	86.7	0
	J48	83.3	8.6
	Naïve Bayes	93.3	8.6

Table 3: Performance of the first stage of the hierarchical classifier

Table 3 and Table 4 report the performance of the hierarchical classifier using the leave-one-out method. As can be seen, SVM [11] provides the best performance among all the applied methods for both the classifier stages. For the first stage, for all subjects the true positive rates remained higher than 82.9% and false positive rates lower than 1.6%. The performance of the second stage classifier has accuracy ranging from 88% to 73.33% when SVM is applied. Testing the system with more subjects is under way.

		Accuracy (%)
Subject 1	SVM	82.86
	J48	80
	Naïve Bayes	76
Subject 2	SVM	88
	J48	80
	Naïve Bayes	68.6
Subject 3	SVM	73.33
	J48	70
	Naïve Bayes	70

Table 4: Performance of the second stage of the hierarchical classifier

VII. CONCLUSION AND ONGOING WORK

This paper reported the design, system structure, and performance for a wireless and wearable food and drink intake monitoring system. The paper presented machine learning based swallow detection method using hierarchical classification scheme. Ongoing work on this topic includes: a) large scale validation of the system and concept with more subjects, b) developing detection and filtering mechanisms for artifacts introduced by movement and speech, c) implementing a real-time swallow detection architecture, and d) combining both time and frequency domain features, and including more features for better performance.

REFERENCES

[1] “WHO | Obesity and overweight,” *WHO*. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs311/en/. [Accessed: 26-Jan-2013].

[2] “Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults - NCBI Bookshelf.” [Online]. Available: http://www.ncbi.nlm.nih.gov/books/NBK2003/. [Accessed: 26-Jan-2013].

[3] B. Dong and S. Biswas, “Wearable networked sensing for human mobility and activity analytics: A systems study,” in *2012 Fourth International Conference on Communication Systems and Networks (COMSNETS)*, 2012, pp. 1 –6.

[4] V. A. Vance, S. J. Woodruff, L. J. McCargar, J. Husted, and R. M. Hanning, “Self-reported dietary energy intake of normal weight, overweight and obese adolescents,” *Public Health Nutr*, vol. 12, no. 2, pp. 222–227, Feb. 2009.

[5] J. Gates, G. G. Hartnell, and G. D. Gramigna, “Videofluoroscopy and Swallowing Studies for Neurologic Disease: A Primer1,” *Radiographics*, vol. 26, no. 1, pp. e22–e22, Jan. 2006.

[6] O. Amft and G. Troster, “Methods for Detection and Classification of Normal Swallowing from Muscle Activation and Sound,” in *Pervasive Health Conference and Workshops, 2006*, 2006, pp. 1 –10.

[7] S. Passler and W.-J. Fischer, “Food Intake Activity Detection Using a Wearable Microphone System,” in *2011 7th International Conference on Intelligent Environments (IE)*, 2011, pp. 298 –301.

[8] P. Alexandre Moreau–Gaudry MD, A. S. Ms, G. B. PhD, and A. F. Md, “Use of Respiratory Inductance Plethysmography for the Detection of Swallowing in the Elderly,” *Dysphagia*, vol. 20, no. 4, pp. 297–302, Oct. 2005.

[9] Bo Dong, Subir Biswas, “Noninvasive wearable diet monitoring through breathing signal analysis,” presented at the SPIE Defense, Security, and Sensing, Baltimore, Maryland, United States, 2013.

[10] S. Baard, S. Kozlowski, R. DeShon, S. Biswas, M. Braun, T. Rench, M. Pearce, D. Bo, and Y. Piolet, “Assessing Team Process Dynamics using Wearable Sensors: An Innovative Methodology for Team Research,” presented at the In press, to Appear,Proceedings of the Annual Conference of the Society of Industrial Organizational Psychology, San Diego, CA, Apr-2012.

[11] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. Wiley-Interscience, 2000.