Towards Continuous Wheeze Detection Body Sensor Node as a Core of Asthma Monitoring System

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Abstract. This article presents a wheeze detection method for wearable body sensor nodes used in management of asthma. Firstly, a short review of current state of telemonitoring in management of chronic asthma is given. A concept of the asthma monitoring system built around a body sensor node analysing respiratory sounds is proposed, with a smart phone as a self-management center and additional sensor nodes for environment monitoring. In search for a wheeze detection algorithm suitable for low power continuous operation on wireless sensor node, a simple algorithm based on the 4-th order linear prediction coefficients (LPC) method is presented. Predictor error energy ratio of Durbin's algorithm is used as the only feature. Algorithm is implemented on low power digital signal processor (DSP) to evaluate its performance. Sensitivity (SE) of 70.9%, specificity (SP) 98.6% and accuracy (ACC) of 90.29% are achieved using pre-recorded test signals. Program complexity is analysed in order to identify possibilities of lowering power consumption.

Keywords: asthma telemonitoring, body sensor networks, wheeze detection, LPC, Durbin's recursion.

1 Introduction

Rising prevalence of asthma increases the workload of medical staff and costs to healthcare systems. The oldest and simplest form of telemonitoring in respiratory disease management is upload of home peak-flow-meter (PFM) data. Clinical deployments and reviews of automated PFM [1], [2] conclude that although patients generally express positive attitude towards this type of management, PFM is unable to capture the moments of the worst airflow obstruction, and requires patient cooperation (nocturnal monitoring). Also, it is common to experience the fall of patient's interest during a long-term monitoring. This stresses the need to automate the management of the disease and intervene in patient's daily routine as little as possible.

On the other hand, maturity of personal wireless area networks such as Bluetooth and IEEE 802.15.4 variants, blooming of the smart phone market, rise of

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interest of mobile providers for machine-to-machine services (M2M) open possibilities for continuous monitoring employing wireless sensor networks on a patient, and/or in the environment. However, key challenges to wider application are:

1. Technical - accuracy, energy efficient long-term operation, reliability;
2. Clinical testing, certification, proof of effectiveness and patient adherence [3];
3. Adoption of adequate business models for deployment of the system.

In this paper we broach the topic of technical issues, first by providing a short overview of current state of the art in asthma telemonitoring. Further, we propose an architecture of the asthma monitoring system. In the second part of the article we focus on the wireless body sensor node for continuous 24-hour telemonitoring and present our current work on signal processing for wheeze detection.

2 Recent Advances in Asthma Monitoring

With the advent of wireless sensor networks (WSN) in the last decade, a number of environmental sensing applications emerged, including those dealing with asthma. Shanoy [5] described the concept of WSN with stationary nodes monitoring levels of gasses potentially triggering asthma. Seto [6] proposes mobile, body-worn nodes for sensing environmental asthma triggers (pollen) in the immediate surroundings of patient and his physical activity. Fu [7] shows the concept of a body-worn sensor network for simultaneous monitoring of triggers in patient's surrounding and respiratory parameters (breath rate). Wisniewski [8] also emphasizes the need of combined monitoring of the environment and the patient and proposes the continuous wheeze monitoring by smartphone. Nanyang University group [9] proposes wearable node with local signal processing for continuous detection of wheezes.

Among mature products offering wheeze monitoring, most recent are the certified products for short-term ambulatory use [10]. Also, much public attention was attracted to the project Asthmapolis featuring indirect collaborative sensing of the potentially dangerous zones by mean of sensorizing asthma-inhaler pumps, and equipping them with GPS/GPRS modules and combining with ubiquitous mobile phones [11]. Also a multitude of iPhone/Android asthma diary applications exist.

3 Architecture of Asthma Monitoring System

Following the review in the previous section, we agree on the significance of both monitoring of respiratory function and monitoring of triggers in the environment and propose system architecture as shown in Fig. 1.

We propose a continuously worn body sensor node as a core of our monitoring system. Continuing our research of power management of wireless sensor nodes [4], we aspire towards the battery operated device with locally implemented signal processing for multiple weeks of autonomous on-board classification of respiratory sounds in real-time. The accent is put on wearability and minimum of intrusiveness and maintenance by user.

Upon detection of abnormal sounds (eg. wheezing), data is sent to the patient's smart phone, used as a presentation layer and data gateway to medical database. Bluetooth peak-flow-meters may be used as an optional device for control. Emphasis is put on self-management of the disease, rather than on direct communication with medical staff (in times of exacerbations). Data is typically accessed by medical staff during patient's scheduled checks, with content and form of presentation also being key elements.

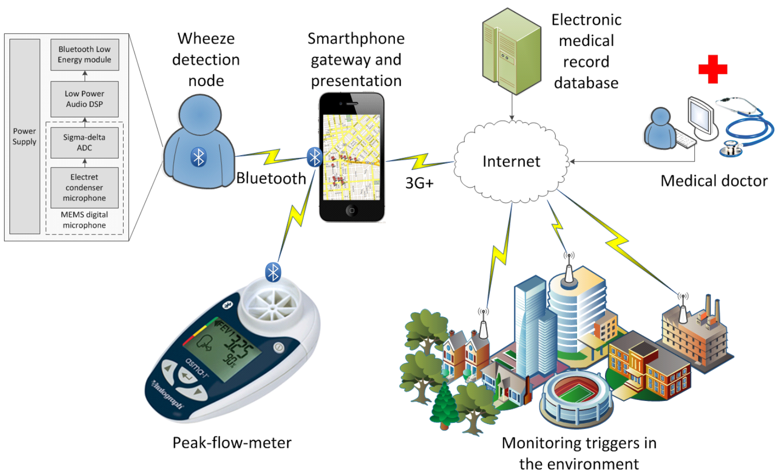

Fig. 1. Architecture of the asthma monitoring system

Asthma triggers are sensed from the environment by stationary nodes. Our preliminary internal study of the off-the-shelf electronic components currently marketed has shown little advance in the field of air quality sensing, with high consumption, low precision MOX gas sensors and bulky optical particulate matter sensors still being state of the art. This restricts the deployment of a feasible body worn network for sensing triggers. Meteorological data, such as air temperature, humidity or pressure, can be monitored by low power digital sensors. Thus, in the rest of this study we focus on the body sensor node for continuous monitoring of wheezes.

4 BSN Node Architecture

Architecture of the BSN node is presented in Fig. 1. It consists of several functional blocks: audio signal acquisition, DSP for local wheeze detection and Bluetooth Low Energy communication.

Major guidelines on acquisition and preprocessing of respiratory signals are defined by [12] and [13]. Both microphone and accelerometer devices are recommended for acoustical signal acquisition. To shorten the analog signal path, we propose an evaluation of the analog capacitive MEMS with integrated amplifiers or digital MEMS microphones with integrated sigma-delta ADC-s. Except antialias filtering, a high pass filter of cutoff frequency around 100 Hz is needed for attenuation of heart sounds.

Bluetooth is proposed for communication between the body sensor node and a smartphone, because of its widespread compatibility and its acceptance among interoperability and standardization bodies. Its main disadvantages are high power consumption and long and complicated pairing/connection protocols. In our scenario, data is transferred to a smartphone only upon the detection of a wheeze. Due to the low data rate and power consumption, we strive to implement Bluetooth Low Energy(Bluetooth 4.0) as a next generation solution.

5 LPC Wheeze Detection Algorithm

Signal processing for asthma management includes wheeze detection, respiratory cycle detection and noise cancellation techniques. In the rest of the text we concentrate on one wheeze detection technique.

Wheezes are continuous adventitious respiratory sounds consisting of a single or a small set of discreet frequencies, of defined duration, superposed on normal respiratory sounds [13]. Thus, wheeze detection converges to the problem of instantaneous frequency estimation. A multitude of short-term Fourier transform (STFT) based algorithms already exist which follow the straight-forward approach of calculating the fast Fourier transform (FFT) of the signal block, calculating power spectrum and applying the set of rules regarding energy distribution throughout the spectrum and duration of spectral peaks [14].

In perspective of implementing the algorithm on a low-power, wireless body-worn sensor node eventually not featuring dedicated FFT coprocessor, one of the ideas is to avoid common FFT based algorithms, and to search for simpler algorithms operating on a minimum feature set extracted directly from the time domain. In this light, we evaluate a variant of the linear predictive coding (LPC).

The method originates from speech coding. It has already been used by several authors in respiratory sounds analysis, mostly for crackle detection, as LPC coefficients exhibit changes correlated to changes in signal waveform [15].

LPC is an autoregressive time domain estimator $\hat{s}[n]$ of current signal sample $s[n]$ based on linear combination of previous p samples and LPC coefficients a_k, $k = 1...p$:

$$\hat{s}[n] = \sum_{k=1}^{p} a_k s[n-k]. \tag{1}$$

Energy of error of the predictor E is taken as a measure of quality of prediction:

$$E = \sum_n (s[n] - \hat{s}[n])^2 = \sum_n (s[n] - \sum_{k=1}^{p} a_k s[n-k])^2. \quad (2)$$

Prediction coefficients $a_k, k = 1...p$, are found by minimizing E, $\frac{\partial E}{\partial a_k}$ which converges to solving a linear equation with p variables. Here, a variant of LPC solver using short-term autocorrelation and Durbin's algorithm is used. Each pass through the Durbin's recursion generates the prediction error energy of that order k, $E^{(k)}$:

$$E^{(k)} = (1 - (a_k^{(k)})^2)E^{(k-1)}, \quad (3)$$

where $a_k^{(k)}$ is k-th prediction coefficient of k-th order. Thus, during process of calculation of LPC coefficients of order p, $E^{(0)}...E^{(p)}$ are produced. $E^{(0)}$ is energy of the analysed signal block (in fact autocorrelation for offset 0). Generally, it can be observed that with each subsequent recursion pass, prediction error energy $E^{(k)}$, $k < p$ exhibit the fall in value. Fall is mostly pronounced for lower orders and is dependent on the analysed signal. Correlated signals with small number of discreet frequency components such as wheezes exhibit higher fall than normal respiratory sounds (wide-band signal). Fig. 2 shows this in form of $E^{(0)}/E^{(k)}$ ratio. Given ratio was used as a feature to classify signals into normal and wheezing class.

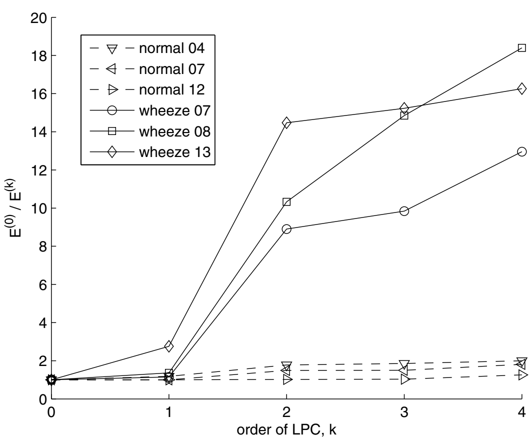

Fig. 2. E(0)/E(k) ratio for wheeze and non-wheeze (normal) signals as a function of the LPC order

6 Materials and Methods

The implementation of the algorithm is depicted in Fig. 3. The algorithm operates on blocks of 256 successive samples sampled by ADC at 2 kHz. FIR filter is used to attenuate hearth sounds. Hamming window is used. Low order of 4 of predictor is used to prevent accumulation of numerical error during implementation of fixed-point Durbin's recursion. For the same reason, dithering noise was added. Special care was taken to detect and avoid overflows. $E^{(0)}/E^{(4)}$ ratio was used as a feature for the classification of respiratory signal. The simplest fixed threshold classification of $E^{(0)}/E^{(4)} > \theta$ was used, with θ empirically determined to be 6.

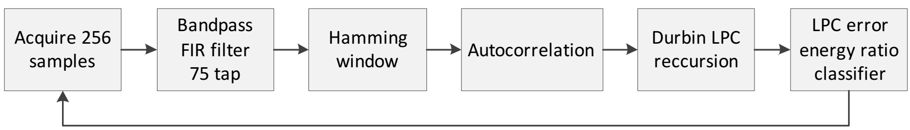

Fig. 3. LPC wheeze detection algorithm

The LPC algorithm was implemented on a 16-bit fixed point DSP TI TMS320-VC5505 evaluation board. The test was conducted by feeding the test signals through evaluation board's analog audio-in interface.

Test signals were acquired from various open-access Internet sources. A total of 13 wheezing signals (W01...W13) and 13 normal signals (N01...N13) of various duration, sampling frequency, SNR, body-locations and of patients of various age and gender were used. Generally, a lack of standard databases of pre-recorded respiratory sounds analysis, for evaluation of algorithms is identified.

Evaluation was conducted by auditory and visual inspection of the spectrogram of all sound recordings. Spectrograms were segmented into inspiratory and expiratory phases. For each segment (respiratory phase), occurrence of wheeze on spectrogram was compared with resulting DSP output stream in order to identify true positive (TP), true negative (TN), false positive (FP) and false negative (FN) regions and calculate sensitivity $SE = TP/(TP + FN)$, specificity $SP = TN/(TN+FP)$ and accuracy $ACC = (TP+TN)/(TP+FP+FN+TN)$. The results were averaged.

7 Results

Results of the testing are given in Table 1. The mean sensitivity of the algorithm was found 70.9%, specificity 98.6% and accuracy 90.29%.

A posteriori analysis of the algorithm performance has been conducted in order to determine hardware constraints for proposed solution. At the operating frequency of DSP of 60 MHz, and audio sampling frequency of 2000 Hz, execution time of one cycle of the algorithm (calculation of one set of 4-th order

Table 1. Performance of the LPC algorithm

File	TP	FN	TN	FP	**SE** [%]	**SP** [%]	**ACC** [%]
W01, N01	4	2	11	2	66.7	84.6	78.98
W02, N02	2	3	13	0	40	100	83.33
W03, N03	2	5	13	0	28.6	100	75
W04, N04	3	0	5	0	100	100	100
W05, N05	2	1	4	0	66.7	100	85.71
W06, N06	2	2	8	0	50	100	83.33
W07, N07	6	0	10	0	100	100	100
W08, N08	3	0	7	0	100	100	100
W09, N09	0	3	9	0	0	100	75
W10, N10	4	0	14	0	100	100	100
W11, N11	13	2	25	0	86.7	100	95
W12, N12	1	0	7	0	100	100	100
W13, N13	2	0	12	0	100	100	100
Total	44	18	138	2	**70.9**	**98.6**	**90.29**

coefficients on 256 samples) is 554,872 DSP cycles. This results in occupying of 7.23% of the DSP time and yields theoretically achievable average consumption of (only) signal processing of 0.85 mA. Duration of the execution is invariant of the outcome of the detection.

8 Conclusion

We have proposed a feasible system architecture of a wireless sensor network for monitoring of asthma, using the state of the art off-the-shelf components.

The proposed LPC wheeze detection algorithm proved to be capable for real-time operation. Due to low workload, the DSP can be theoretically put to standby for more than 90 % of the duty-cycle or algorithm can be implemented on the platforms with significantly lower power consumption (where FFT may not be applicable).

Main drawback of the algorithm is its inherently low sensitivity due to the simple feature set capable of detecting only the degree of correlation of the signal. Thus, method can not be implemented as a trigger for another high sensitivity method as relatively great amount of wheezing blocks are interpreted as normal (non-wheezing).

In the future we plan to investigate the improvement of sensitivity by extending the feature set and employing more sophisticated classifiers. Also, extensive testing of the operation of the algorithm in conditions of low SNR, comparison of the performance with the STFT based algorithms and detailed evaluation of power consumption are required.

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References

1. Ostojic, V., Cvoriscec, B., Ostojic, S.B., Reznikoff, D., Stipic-Markovic, A., Tudjman, Z.: Improving asthma control through telemedicine: a study of short-message service. Telemed. J. E Health 11, 28–35 (2005)
2. Jaana, M., Paré, G., Sicotte, C.: Home telemonitoring for respiratory conditions: a systematic review. Am. J. Manag. Care 15, 313–320 (2009)
3. Bonfiglio, A., Rossi, D.D.: Wearable Monitoring Systems. Springer, Heidelberg (2011)
4. Oletic, D., Razov, T., Bilas, V.: Extending lifetime of battery operated wireless sensor node with DC-DC switching converter. In: IEEE Instrument. and Measurement Tech. Conf. I2MTC, Hanzhou (2011)
5. Shenoy, N., Nazeran, H.: A PDA-based Network for Telemonitoring Asthma Triggering Gases in the El Paso School Districts of the US - Mexico Border Region. In: Proc. 27th Annual Int. Conf. of the Engineering in Medicine and Biology Society IEEE-EMBS, pp. 5186–5189 (2005)
6. Seto, E.Y.W., Giani, A., Shia, V., Wang, C., Yan, P., Yang, A.Y., Jerrett, M., Bajcsy, R.: A wireless body sensor network for the prevention and management of asthma. In: Proc. IEEE Int. Symp. Industrial Embedded Systems SIES 2009, Lausanne, pp. 120–123 (2009)
7. Fu, Y., Ayyagari, D., Colquitt, N.: Pulmonary disease management system with distributed wearable sensors. In: Proc. Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society EMBC, Minneaplolis, pp. 773–776 (2009)
8. Wisniewski, M., Zielinski, T.: Digital analysis methods of wheezes in asthma. In: Proc. Int. Signals and Electronic Systems (ICSES) Conf., Gliwice, pp. 69–72 (2010)
9. Ser, W., Yu, Z.-L., Zhang, J., Yu, J.: Wearable system design with wheeze signal detection. In: Proc. 5th Int. Summer School and Symp. Medical Devices and Biosensors ISSS-MDBS, Hong-Kong, pp. 260–263 (2008)
10. Karmelsonix Website, `http://www.karmelsonix.com/`
11. Asthmapolis - asthma inhaler tracking, `http://asthmapolis.com/`
12. Pasterkamp, H., Kraman, S.S., Wodicka, G.R.: Respiratory sounds. Advances beyond the stethoscope. Am. J. Respir. Crit. Care Med. 156, 974–987 (1997)
13. European Respiratory Review. European Respiratory Journal (2000)
14. Alic, A., Lackovic, I., Bilas, V., Sersic, D., Magjarevic, R.: A Novel Approach to Wheeze Detection. In: Proc. World Congress IFMBE, pp. 963–966 (2007)
15. Bahoura, M.: Pattern recognition methods applied to respiratory sounds classification into normal and wheeze classes. Computers in Biology and Medicine 39, 824–843 (2009)