Wireless sensor networks in monitoring of asthma

Dinko Oletic
Faculty of Electrical Engineering and Computing
University of Zagreb
Unska 3, Zagreb HR-10000
Email: dinko.letic@fer.hr

Abstract—Asthma is one of the widespread chronic diseases. Rising prevalence increases the burden of personal disease management, financial expenditures and workload, both on sides of patients and healthcare systems. Firstly, the medical background of asthma is given. Pathology and symptoms are presented. Afterwards, the problem of persistent asthma management is introduced with a short overview of traditional disease management techniques. A review on approaches to asthma telemonitoring is made. Effectiveness of home peakflowmetry is analysed. Employment of low power wireless sensor networks (WSN) paired with smartphone technologies is reviewed as a novel asthma management tool. Using the technology, the aim is to retain the disease in a controlled state with minimal effort, invasiveness and cost, and assess patient's condition objectively. WSN-s for sensing of both asthma triggers in the environment, and continuous monitoring of physiological functions, in particular respiratory function are reviewed. Sensing modalities for acquiring respiratory function are presented. Signal acquisition prerequisites and signal processing of respiratory sounds are reviewed. Focus is put on low-power continuous wheeze detection techniques. At the end, research challenges for further studies are identified.

Index Terms—asthma telemonitoring, body sensor network, peakflowmetry, asthma diary, respiratory sounds analysis, wheeze detection

I. INTRODUCTION

Together with diabetes and chronic heart diseases, chronic pulmonary diseases are mostly common group of chronic diseases. Among pulmonary disorders, asthma is one of the highly represented. It is estimated that 300 million people worldwide suffer from asthma [1]. About 10% of overall children population suffer from asthma. By 2025, it is estimated that the number of patients with asthma will grow by more than 100 million [2]. With rising prevalence, the expenditures of healthcare system for patient treatment are expected to rise, together with workload of the medical staff.

A. Definition, pathology and symptoms of asthma

Asthma is defined as a chronic hypersensitivity of the bronchial airways. It manifests as recurring periods of obstruction exacerbations (attacks) and calming periods. The symptoms in the attacks include wheezing, shortness of breath (dyspnea), chest tightness, cough. They emerge as a consequence of contraction of the tracheobronchial smooth muscles (bronchospasm), oedema and hyper-secretion of mucus, and result in narrowing of the airways (bronchoconstriction) [3], as shown in Fig. 1.

Fig. 1. Manifestation of asthmatic bronchoconstriction [4]

Type of asthma is determined by source of bronchial hypersensitivity: allergic asthma (atopic, extrinsic, caused by immunologic stimulus of an antigen), intrinsic (nonallergic, induced by infection, physically or chemically), exercise induced, drug induced asthma, occupative asthma and asthmatic bronchitis. About 70% of asthmatics suffer from allergies [1]. In this study we mainly focus on the allergic asthma, but methods proposed apply to all forms of asthma which include occurrence of wheezing. In allergic asthma, immunoreaction is induced by triggers from the ambient: pollen from trees or grass, smoke, dust-mites, feather, fur, meteorological conditions etc. It is often seasonally related. For every patient, sources of immunoreactivity are specific and are determined by allergologic testing. Bronchial hyperreactivity is quantized by conducting a bronchial challenge tests using methacoline or histamine as provocators. Functional tests are carried out with ambulatory spirometers to assess the level of bronchoconstriction [5].

Several types of medications are used for treatment of asthma. For immediate effect during attacks, short acting \( \beta_2 \)-adrenoceptor agonists and/or anticholinergic bronchodilators are used. For long-term prevention, glucocorticoids and long acting \( \beta \)-adrenoceptor agonists (in combination with steroids) are issued. In allergic asthma, hyposensibilization is conducted seasonably [5].

Asthma severity in regard to the frequency of the symptoms (attacks) is classified into four stages, according to GINA guidelines [5]:

1) intermittent - light cough and wheezing less than twice per week, night symptoms less than twice per month,
2) mild persistent - attacks at least once per week, chest
tightness, shortness of breath, coughing and wheezing,
3) moderate persistent - affects the larger passageways in
the lungs and trachea, intensified episodes of coughing
and wheezing,
4) severe persistent - episodes during both day and night
occur continually and can last for more than several
days, persistent cough and wheeze.

II. TRADITIONAL PROCEDURES OF ASTHMA
MANAGEMENT

Recurrence of the asthmatic attacks leads to irreversible
advancement of the disease into the subsequent stage. The goal
of daily management of asthma is retaining the disease in the
diagnosed stage and prevention of further progression. Thus,
it is necessary to ensure long-term adherence of the patient
to the chronic disease management plan.

Traditional procedures of asthma management in most cases
consist of adherence to the intake plan of prescribed med-
ication including both preventive and emergency medication,
avoidance of diagnosed triggers in the environment, periodical
pulmonary function self-assessment and periodical check at
the medical specialist for evaluation of the level of control.

Paper written asthma diaries of types and times of occur-
rence of the symptoms and amounts of medication taken are
the traditional way of patient monitoring, common to chronic
diseases in general. Due to patient’s and medical specialist’s
overhead, such diaries are commonly practised only on limited
groups, for a limited time during clinical studies.

In combination with diaries, simplest mechanic peak-
flowmeter devices (PFM) are issued for management at home,
for self-assessment of severity of airflow obstruction. They
are simplified version of ambulatory spirometers for home
use. Featuring limited accuracy, they are able to estimate a
limited set of spirometric parameters: PEF (peak expiratory
flow [L/s]) and FEV-1 (forced expiratory volume of the
air exhaled in the first second [L]). Best value is always
taken as a final result of particular measurement session.
Measurements are typically conducted in the morning and in
the evening to show diurnal variability between measurements.
Results of the measurement in the morning are usually worse,
and often reflect night symptoms (nocturnal asthma). Results
are typically divided into simple colored zones to simplify
interpretation - e.g. red, yellow and green typically resembling
80-100%, 60-79% and <60% of full scale respectively [6].

With the goal of reducing asthma management overhead
of all groups involved (patient, caregiver, health insurance),
approaches to telemonitoring systems for asthma management
are presented in next section.

III. TELEMONITORING OF ASTHMA
A. Automation of peakflowmetry and asthma diaries

Upload of home PFM data is the oldest and simplest form
of telemonitoring in respiratory disease management. One of
such works is medical study by Finkelstein from 2000 [7].

The simplest form is the use of mechanical PFM, along with
manual input of the PFM results and subjectively perceived
symptoms. One approach was transmission of data by SMS.
A research of feasibility and adherence of such system was
conducted in [8]. Alternative approach to manual input were
asthma web portals, at the time widely accessible mainly from
stationary PC-s. Websites accompanied PFM upload, diary of
symptoms and medication, revision of the individual treatment
plan by medical specialist, and static information for education
of the patient [6].

Recent studies propose smartphones with goal to simplify
user interaction and integration of asthma management proce-
dures in patient’s daily routine [9]. This paper proposes easy
to use touch-screen interface, PEF and subjective symptoms
questionnaire, daily information on asthmatic triggers (temper-
ature, humidity, suspended particulate matter) streamed from
the public sources based on GPS location and potentially a
sensorised inhaler for medication monitoring.

Automation of PFM data entry by Bluetooth (or at least
RS232) connectivity to a personal computer or mobile phone
increases the adherence in long-term studies. Cobern [10]
conducted an extensive study including two field tests of
feasibility of electronic peakflowmeters connected to mobile
phones. Several reviews of automated peakflowmetry were
made [9], [11], [12]. In all reviews, it is concluded that
patients generally express positive attitude towards this type
of management.

Regarding medical value of PFM in asthma monitoring, [13]
reports on relationship between measured airway obstruction
and subjectively perceived general condition. As subjectively
perceived symptoms often correlate poorly to objective airway
obstruction in adult asthmatics, PFM is a desirable mean of
long-term management.

On the other hand, there are disadvantages of home peak-
flowmetry as a monitoring tool, first being lower precision than
spirometry, especially when it comes to correlation of FEV-1
with obstruction of lower airways. The second is fact that it
demands patient’s participation and the results can vary based
on his effort (maximal expiration). Finally, the most important,
it assesses the condition of the patient in discreet moments,
missing the moments of the worst airflow obstruction [14].
This stresses the need for continuous monitoring.

B. Monitoring of triggers in the environment

With the advent of low power wireless sensor networks, it
has become possible to continuously monitor two sources:
1) immediate surrounding of the patient for triggers, and
2) patient’s physiological functions.

An example of portable but stationary sensor nodes, mon-
itoring levels of asthma triggering gasses is given in [15].
Gas sensors were wired to a PDA and data was sent via
Bluetooth to a PC maintaining database. In today’s terms, the
solution seems not very applicable due to the limited range of
Bluetooth, high cost, high energy consumption and bulkiness.

A step further are the concepts of body worn sensor node for
sensing the triggers in the immediate surrounding of
the patient. Examples of such systems is Asthma Vest [16]
for monitoring of the air quality by sensing concentration
of formaldehyde, carbon dioxide, ozone, nitrogen dioxide, temperature, relative humidity, and total volatile organic compounds. The node has been carried in the pocket. Conceptually similar is the waist-worn sensor board consisting of optical sensor for airborne particles (dust, pollen), temperature and humidity by SHARP [17]. Another example is the WSN platform DexterNET consisting of technologically heterogeneous devices [18]. At the body level, system consists of a wired bulky hand-held particle monitor carried in a backpack, Bluetooth GPS, and 802.15.4 wireless sensor node for physical activity tracking (aimed at exercise-induced and allergic asthma). The project introduces a concept of participatory sensing in form of sharing the information on particulate matter distribution with other users of the system. This enables generation of real-time distribution geo-maps with finer temporal and spatial resolution on the points of interest, than with a network of static sensor nodes.

The similar model is followed by project Asthmapolis [19]. There, the potentially dangerous zones are collaboratively sensed indirectly, by monitoring the places where asthmatic attacks occur and medication is taken. This is achieved by sensorising asthma-inhaler pumps, equipping them with GPS/GPRS modules, and combining them with appropriate web-application for presentation [19]. Issues of exposure of the private geolocational information through a participatory/collaborative network emerge.

Study of the recent off-the-shelf electronic components 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. Only meteorological data, such as air temperature, humidity or pressure, can be monitored by low power digital sensors.

As the exact influence of various triggers in the immediate surrounding of the patient (and change of the susceptibility to particular triggers) has not yet been objectively determined in clinical research, measurement of the triggers in the immediate environment is needed for long-term medical studies in the first place.

C. Monitoring of patient’s physiological functions

Possible candidates for physiological function monitoring in asthma include respiratory rate (both frequency and duration of respiratory phases), heart rate, $SpO_2$, and detection of wheezes. A concept of wearable body area network (BAN) for pulmonary disease management, monitoring both physiological and environmental parameters is presented in [17]. $SpO_2$, and physical activity (accelerometer) are monitored. System also features acoustic body-worn sensors for monitoring of breathing frequency, durations of inspirations/expiration and heart rate. With wheezing being most specific symptom for asthma, systems for wheeze monitoring are put in the focus.

1) Clinical significance of wheezing: Wheezes are high-pitched musical adventitious sounds originating from fluttering of the nearly closed constricted airways. Wheezing is mostly present in mild to severe asthma. It is a certain indicator of asthmatic attack in progress. In asthma, wheezes are most characteristic for expiration [5].

Strongest correlation between the presence of wheeze and bronchial obstruction is obtained through wheeze rate, which expresses percentage of the respiratory cycle occupied by wheeze ($T_{wheeze}/T_{cycle}$) [20]. Occupancy of at least 3% of respiratory cycle by wheezing should be indicator of light airway constriction and onset of attack. In the attacks, maximal wheeze rate is reported to reach about 25 to 35% [14].

Advantage of wheeze monitoring over FEV1 is the ability to assess respiratory function effortlessly (children, elderly), during tidal breathing, and possibility of continuous monitoring, also during sleep. It should be intended for patients with mild constriction [14].

Attention needs to be taken when correlating it to standard spirometric results. A study of correlation of occurrence of wheeze and spirometric data comparing the dose of methacholine at which FEV1 falls by 20% (PC20-FEV1) with the dose of methacholine at which wheezing occurs (PCW) during the bronchial provocative tests on preschool children [21] states that wheezing is a less sensitive parameter than change in FEV1. It is reported that on average, PCW was about 2.5 times higher than PC20-FEV1. Also, the average time to reach PC20-FEV1 was reported 30% shorter than to reach wheezing.

The review of literature in [22] supports the thesis of lower sensitivity of wheezing than FEV1, reporting the PCW to be approximately 1.5 times greater than the PC20-FEV1 in study carried on adults. Conclusion is that lower sensitivity and high variability among patients is preventing factor for wheeze rate to be used as a precise predictor of FEV1.

In some patients, wheezing is not present and shall not be used as the only relevant symptom. Namely, most patients with asthma complain more frequently about chest tightness than on wheezing, and in some patients, wheezing can be provoked only during forced expiration. Wheezing is also absent in many patients with significant airway obstruction. This condition is known as “silent chest” [3]. Besides wheezing, changes in lung sounds during flow obstruction can be recognized on other parameters of auscultation, most noticeably a decrease in breath sound intensity, change in breathing rate and increase of the duration of expiration [5]. This indicates the need of tracking additional respiratory parameters along with wheezing.

2) A review on telemonitoring systems for wheeze monitoring: The most primitive system features local recording only and transmission of the sound for analysis. The study of [23] describes such mobile phone based system for manually initiated measurement of respiratory sounds by placing a microphone on the trachea and transmitting the results in form of a voice-mail. Automatic wheeze detection is implemented on the back-end server. Such monitoring on demand did not offer continuous tracking. Also, no immediate feedback for patient is present.

Wisniewski [24] shortly systematizes the evolution of asthma management, starting from home peakflowmetry, over monitoring of environment, to wheeze detection and stresses
Fig. 2. Proposed asthma monitoring system architecture

the need for parallel tracking of both triggers in the environment and wheezing. In his work, acoustical monitoring of respiratory function is achieved by coupling a set of two microphones to a smartphone where signal processing is conducted.

Group at Nanyang University is focused on wearable node with local signal processing for continuous detection of wheezes. In 2008 Ser [25] described the prototype of a wearable system featuring the array of microphones (for beam forming) and an on-board signal processing using a DSP. PDA is used for displaying the results and communication with Internet server. His work was continued in 2009 by improving the wheeze detection algorithm [26], and with study on noise cancellation [27].

Among mature commercial products offering wheeze monitoring, most recent are the certified instruments for ambulatory use (Pulmotrack, Wheezometer) and holter devices WHolter (a dedicated signal processing unit, microphones are attached by wires, used in diagnosis of nocturnal asthma) [28]. Also, hand-held PDA-based wheeze detection tool, and a multichannel device for acoustical tomography of lungs are offered to aid medical specialists in diagnosis [29].

From the review, it can be concluded that typical asthma monitoring system is structured of elements shown in Fig. 2:

1) a body sensor node for respiratory function monitoring,
2) electronic asthma diary on mobile phone,
3) electronic peakflowmeter,
4) sensors nodes for trigger monitoring in the environment, and
5) remote server with database,

In the next sections, we focus on review of architecture of body-worn wireless sensor node for continuous respiratory function monitoring, serving as a basis of WSN for management of asthma. Respiration function assessing techniques, signal processing and communication subsystems are presented.

IV. SENSOR TECHNOLOGIES FOR CONTINUOUS RESPIRATORY FUNCTION MONITORING

A. Sensing modalities

There are several modalities for monitoring of respiratory function:

1) Ultra wide band radio technology (UWB): Intense research has been done recently in the field of ultra-wide band technologies for medical applications. UWB is primarily used for radar imaging. It can be used for detection of lung wall movement. Due to low power consumption, it can be integrated in wireless sensor networks. Its advantage is contactless measurement indifferent to noise induced by movement of the body/clothes over the sensor, but the shortcoming is that it cannot differentiate wheezes which are specific symptom for asthma, but only measure the respiratory rate [30], [31].

2) Forced oscillometry: Forced impulse oscillometry is form of an active respiratory measurement in which small external pressure signal is superimposed on the spontaneous breathing, and the resulting airflow of respiratory tract is observed. Compared to conventional spirometry, advantage of the method is that it can be conducted during tidal breathing and thus requires less cooperation of the patient. On the other side, it is not suitable for continuous monitoring as it requires a mouthpiece for measurement of the flow and impulse sound can induce discomfort to the patient. Also, the generation of actuating pressure signal increases power consumption [32].

3) Mechanical vibrations sensing: Two methods of sensing mechanical vibrations are present [33]:

- contact method is achieved by an accelerometer placed in direct contact with skin surface. The vibrations produced by air stream are conducted through the lung wall to the skin surface. The firm contact and no movement of sensor with respect to skin needs to be ensured.
- contact-less sensing via microphone. In this case, an air cavity is formed between skin and the sensor. Vibrations of the chest wall generate variations of pressure level. Pressure is conducted through the cavity and sensed by a membrane. Majority of researchers prefer microphones because they are less susceptible to artefacts produced by skin movement, do not feature resonance and have lower price.

B. Standards in acquisition of respiratory sounds

A review has been conducted on microphones [34]. Flat response in the frequency range of respiratory sounds (100-2000 Hz), high sensitivity, and low noise is desired. Capacitive microphones are concluded to offer the best trade-off between parameters. General guidelines on requirements are reviewed in [20].

Emerging from the mobile phone applications are IC MEMS sensors with capacitive membrane. Two types are present on the market: (1) analog sensors with integrated operational amplifier and (2) digital variants integrating sigma-delta converter, featuring the pulse-density modulated digital output signal.
A conical cavity of 2.5-5 mm in depth and 10-15 mm in diameter with circumferential adhesive ring been proposed for acoustical impedance matching between membrane and the skin surface [33].

An instrumentation amplifier is typically used for analog signal conditioning. A bandpass filter is used to attenuate heart sounds of <100 Hz, and serve as an anti-aliasing filter at \( F_s/2 \) (typically 2000 Hz). A 4-th order is chosen in most reports as a tradeoff between reasonable attenuation in stopband and noise.

A 12-16 bit ADC is proposed for signal conversion. Sampling frequency is selected accordingly to signal processing technique, with frequency range of respiratory signals in range of 100 to 2000 Hz.

Generally, low SNR of the analog sensing circuit increases the demand on signal processing in digital domain [35]. Weighting between analog preprocessing (in hardware) and digital signal processing (software) during design of the sensor node architecture can thus be observed as a mean of power management.

Location of placement of the sensors are evaluated. Tracheal sounds are reported stronger in amplitude and cover wider frequency range of up to 1500 Hz [36]. Chest wall on the other hand acts like a low pass filter attenuating frequencies above 500 Hz. Overall, great variability of the amplitude and frequency characteristic is reported between various locations [33]. Also, lower sensitivity is reported behind hard tissue (bones).

V. SIGNAL PROCESSING OF RESPIRATORY SOUNDS

Several reviews of the respiratory sound detection and classification algorithms have been made. One of the most recent and most comprehensive is the work of Reichert in course of the ASAP project [37]. Also, Bahoura brought the review of the respiratory sounds classification algorithms from the pattern recognition point of view [38]. In his work, several feature extraction techniques - Fourier transform, linear predictive coding, wavelet transform and Mel-frequency cepstral coefficients (MFCC) were combined with various classification methods: vector quantization, Gaussian mixture models (GMM) and artificial neural networks and the resulting algorithms were evaluated. A combination of MFCC and GMM yielded highest combination of sensitivity, specificity and accuracy in classification of wheeze. Hadjileontiadis [39] gives an overview on advanced algorithms including utilization of higher order statistics like bicoherence index, and empirical decomposition methods such as Huang-Hilbert transform. However, information on the performance is not given.

As one of the key constraints of the wearable node is long-term operation in the environment of constraint energy, in the following section accent is put on the most representative algorithms applicable on low power sensor node for real-time operation.

A. Metrics and evaluation of the algorithms

Extensive metrics for evaluation of respiratory algorithms is given in [38]. Statistical measures as sensitivity, specificity, accuracy are defined. ROC diagrams are proposed. Statistical hypothesis testing is presented in order to test the significance of the results.

A lack of standard databases of pre-recorded respiratory sound analysis, for evaluation of algorithms is identified. About two dozen sounds can be freely accessed over Internet. Many of them origin from the R.A.L.E. [40] educational software for training of pulmonary specialists. MaRS [41] is the University of Marburg’s Respiratory Sounds database, created during early 2000’s and houses data collected off the more than 50 asthmatic patients. Also, during French ASAP project [37], a database was created. Unfortunately, nor MaRS nor ASAP databases feature open access, so many researcher rely on a few sounds fetched from the various Internet sources. One of our goals is to progressively build the database of respiratory sounds, along with extensive information of the patient data and recording conditions. This would ensure reproducibility of previously published algorithms.

B. Respiratory cycle detection

Respiratory cycle detection is needed for multiple purposes: (1) breath-rate determination, (2) detection of the extension of the expiration, (3) calculation of the wheeze rate.

The standard method of respiratory cycle extraction consists of calculation of envelope of the time domain signal and search of pauses between the phases. [42] implements the method using Hilbert transform. Excelent sensitivity of 98% and specificity of 99% are reported.

Fu [17] in his body-worn system proposes the simple method consisting of two steps: (1) envelope detection is performed on the time-domain respiratory sound recorded on trachea, which produces quasi-periodic function with crests representing inspiration, (2) autocorrelation is performed on envelope by which beginnings and the ends of the inspiration are determined. Performance of the algorithm both in term of accuracy and performance remain to be tested as it seems that method has been applied only in Matlab.

Yadollahi and Moussavi developed a noninvasive flow estimation technique based on respiratory sound analysis. In [43] they have shown that a model can be established between Shannon’s entropy of the sound and airflow measured by pneumotachograph. Only one respiratory cycle is necessary to determine parameters of the model. Probability density functions (PDF-s) are needed for calculation of the entropy. In [44], calculation of PDF-s was identified as the bottleneck of the algorithm. By studying the influence of variation of amplitude of the signal on entropy, it has been found that change in amplitude of the signal by factor \( m/n \), decreases the entropy by \( \log n \), with \( n \) being \( \max(\text{segment}) - \min(\text{segment})/N_{\text{fft}} \). This greatly simplifies the flow tracking and enables a simple mean of respiratory cycle tracking, including inspiratory and expiratory phases.

C. Wheeze detection algorithms

Wheeze is continuous adventitious sound heard as musical sound superimposed to the sound of normal breathing. Thus, it can be represented as in Fig 3.
In frequency domain, it is represented as a single peak (or one main peak in parallel with several peaks of lower amplitude in case of polyphonic wheezes). Various authors define various minimal duration and frequency range of a wheeze. The CORSA [20] defines the minimal wheeze duration to be >100 ms and minimal frequency >100 Hz.

In addition to wheezes, several similar adventitious sounds may be present: stridor is similar to wheeze, it can be heard in the environment. Stridor is usually present in inspiration phase. Rhonchi are grinding, but continuous polyphonic sounds, with frequency <200 Hz. Rhonchus usually exhibits multiple higher harmonics. Its appearance is connected to constriction of upper airways. Whistles are high-pitched sounds, similar to wheeze, but of frequency >1200 Hz.

Regarding the definition of wheeze in frequency domain, algorithms involving wheeze detection converge to the problem of estimation of the dominant frequency.

1) *STFT based decision list methods*: Following definition of the wheeze, the classical approach to wheeze detection consists of decomposition of the sound using short-time Fourier transform (STFT) and detection of spectral peaks in the expected frequency band, followed by classification based on a set of rules taking into account duration and temporal and spectral continuity of the peaks [36].

STFT is estimator of temporal frequency content of the signal. STFT of discrete-time signal \( s[n] \) is defined as:

\[
S[m,k] = \sum_{n=-\infty}^{N} s[n] w[n-m] e^{-j2\pi nk/N}
\]  

with \( s[n] \) being the signal, \( w[n-m] \) being the window. In real-time implementations, STFT is typically calculated by FFT on the consecutive blocks of 256-1024 samples (minimum wheeze duration is defined as 100 ms) with signal multiplied by Hamming window and with 50% overlap between consecutive blocks. After FFT, power spectrum density (PSD) \( P_s[m,k] \) is estimated:

\[
P_s[m,k] = \frac{1}{N} |S[m,k]|^2.
\]

The disadvantage of STFT is uncertainty of its time-frequency resolution. Increase of frequency resolution decreases the time resolution and vice-versa.

A classic approach to wheeze detection using STFT is presented in [45] and [46]. STFT is followed by subtracting the trend of the signal estimated by box-filtering from the total signal in order to attenuate baseline (breathing) noise and accentuate peaks. Box-filtering is achieved simply by replacing each value by the average value of its surrounding neighbours. Further, signal is divided into frequency bands and for each band, empirical threshold coefficient is defined. Peaks are extracted when their amplitude exceeds the mean value of the spectrum added by standard deviation multiplied by the coefficient of the frequency band. Classification consists of evaluating four rules: (1) grouping in the band of maximally 70 Hz, (2) parallel coexistence of no more than three harmonics, (3) grouping of the peaks in time, and (4) duration of more than 150 ms. The method was intended as a diagnostic aid for pulmonary specialist and thus involves inverse STFT to the sole, filtered wheeze sounds. The algorithm is said to be amplitude independent, but the empirically sub-band coefficients imply the requirement for training and reflect the characteristics of the training set.

A very similar algorithm called "LAWDA" was presented in [47]. The spectrum of each block is also divided in sub-bands. Detrending of every sub-band is done by subtracting the average value. Every sub-band is normalized by standard deviation and fixed thresholds are used to classify spectrum samples as peak candidate. Candidates are further evaluated by a set of rules each contributing to score. The peak with highest score is elected as wheeze. All coefficients were also fixed.

Qui [23] and Banik [48] approaches to the a problem from viewpoint of detecting tonal signal masked in a coloured noise of normal breathing and proposes "Frequency Duration Dependent Threshold" algorithm. They apply peak detection algorithm by comparing difference of the signal energy and noise energy with the frequency dependent threshold. Afterwards, minimum duration rule is applied and only audible peaks are kept.

2) *Other PSD based approaches*: An attempt is made to avoid the use of fuzzy rules based on thresholds. Correlation coefficient (CC) is a measure of independence of the two random variables. In [49], power spectrograms calculated by STFT of two consecutive blocks of signal are treated as realization of two random variables. Their correlation coefficients are calculated and fixed threshold of CC 0.9 defined. In case of wheeze, CC of consecutive spectra will have value near 1 due to the correlation of their spectra. Although authors present it as a self-sufficient method, the main problem of this algorithm is the inability to discriminate wheezes from other sounds yielding statistically dependent spectra which also produce high CC. Thus, the CC technique may be used only as a part of more selective technique, e.g. as a first discriminator in order to prevent further complex classification on the areas where wheezes are unlikely.

Entropy of the power spectrum can be used as a feature. In [26] each power spectrum was filtered by averaging filter,
divided into bands, relative power of each band \( p_n \) was calculated using the absolute power of the peaks \( c_n \) and finally Shannon’s entropy \( E \) of the relative powers of the bands was determined:

\[
E = - \sum_{n=1}^{N} p_n \log_b p_n, \quad (3)
\]

\[
p_n = \frac{c_n}{\sum_{n=1}^{N} c_n}, \quad n = 1, 2, ..., N \quad (4)
\]

The method is physically valid, as wheezing exhibits grouping in energy in the narrow frequency band of the spectrum. They investigate various feature sets: the difference and ratio between the maximal and the minimal entropy. The advantage of the method is low complexity, and single threshold for classification. 85% of true positives are reported at SNR of 6.

Some authors approach the wheeze detection from the image processing point of view. In [50], the spectrogram is treated as an image. Firstly, noise is removed by applying averaging 2D bilateral filter with property of preserving edges. Then, horizontal Prewitt filter is applied to augment horizontal edges of monophonic signals continuous in time. After that, gaps, small holes, gulfs etc. are closed to form surfaces of potential wheeze positions (so called image closing, opening and mask generation). Classic rules addressing duration and frequency of wheeze are applied. The method is characterized by sensitivity and specificity of 96% and 90% respectively, but due to high processing power demand it is intended for use on a PC as a diagnostic aid to physician. Another example of applying image processing techniques is given in [51].

3) **Time domain signal power estimation**: Some authors seek time-domain analysis techniques, to avoid FFT. Group of Nanyang University evaluated algorithms for use in wearable systems for continuous analysis of wheezes. [27] proposes low sampling rate of 1000 Hz, speech attenuation by beam forming, estimation of signal power and division of the signal in \( N \) bands by filtering in time domain and comparison of the relative powers of each band to the total power of the signal. The linear discriminant analysis is used for classification with over 90% accuracy in presence of speech, and processing power constraints are determined below 1 MIPS.

4) **Wavelet algorithms**: Wavelet transform is often used because it allows for construction of a set of time-domain digital filters instead of FFT for signal decomposition into frequency bands. Two realizations are proposed in the review of Bahoura [38]: (1) wavelet packet transform obtained by iteration of both low and high-pass branches (both detail and approximation branches) on every level to obtain equal-bandwidth frequency bands (2) perceptual wavelet packet transform used as a approximation of Mel-scale frequency division in their subband-based cepstral feature extraction method.

A concept of portable wheeze detector implemented in FPGA is presented in [52]. 4-level, Daubechies 4 taps orthogonal wavelet filter bank is used. Relative change over energy of the output of each filter (energy of each frequency band) is used for classification. The algorithm performance is not reported.

5) **Linear prediction coding (LPC)**: Linear prediction coding originates from auditory tract modelling. It is often used in speech coding. The method predicts the current sample \( \hat{s}[n] \) from the linear combination \( p \) coefficients \( a_k \) and previous samples \( s \):

\[
\hat{s}[n] = \sum_{k=1}^{p} a_k s[n-k], \quad (5)
\]

\[
e[n] = s[n] - \sum_{k=1}^{p} a_k s[n-k] \quad (6)
\]

The predictor coefficients \( a_k \) are solved by minimizing the mean-square estimator error \( e[n] \) derived from \( e[n] \). This converges to Durbin’s recursive algorithm in which short-term autocorrelation is calculated. Algorithm is interesting for respiratory sound analysis as it is a pure time-domain algorithm (avoiding FFT) and builds minimal feature set constituted typically of coefficients \( a_k \) an mean-square predictor error \( e[n] \).

Sankur [53] reviews autoregression in respiratory signal analysis. High accuracy of 93.75% is reported for classification of sounds in normal and pathologic group (containing both patients with crackles and wheezes), but no specific information is given regarding wheezing.

Works [54] and [55] use 6-th order autoregression model for crackle detection. As they are represented as short peaks in the time-domain, prediction coefficients exhibit significant change upon their appearance and can be used as a feature. Although detection of wheeze on the other hand, exhibits no measurable change in coefficients, ratio of the energy of the original signal to the prediction error energy of order \( p \epsilon_0/\epsilon_p \) can be used as a distinctive feature. Nevertheless, mentioned feature is only a detector of correlated signal. In case of the detection of correlated signal, LPC could be extended to estimate frequency of the peak by calculating line spectral pairs (LSP).

**D. Noise cancellation**

Ser from the University of Nanyang group describes the beam forming technique by employing three microphones - two air conductive on the trachea and one bone conductive on the [27]. Algorithm was evaluated in conjunction with algorithm [26] in condition of -5 to +10 SNR with true positives and true negatives not falling below 85%. Independently of SNR test, utilization of (third) bone conductive microphone was tested. It showed as much as 20% better detection than in case of only two air-coupled microphone. Program complexity is reported being high ( 2 s in Matlab on PC).

**VI. WIRELESS COMMUNICATION**

Besides the ability to connect the node to the Internet gateway, in medical applications, communication protocols must adhere to standards. Bluetooth is standard for wireless communication between a body sensor node and a smartphone,
because of its widespread compatibility and its acceptance among interoperability and standardization bodies [56]. Also, certified Bluetooth stacks featuring Health Device Protocol are provided. Its main disadvantages are high power consumption and long and complicated pairing/connection protocols. In the scenario of the node where data is processed locally and is transmitted only upon the positive detection of abnormal lung sounds, low data rate suffices. So, upcoming Bluetooth Low Energy (Bluetooth 4.0) is suitable for such applications. ZigBee is also becoming interesting with the advent of ZigBee Health Care Profile. A major obstacle is lack of complementary transceivers on smartphones.

VII. CONCLUSION

Asthma has been identified as one of the most common chronic disease with the rising prevalence. The key to successful management of asthma is retaining it in the diagnosed state. Traditional methods of home management by peakflowmetry and paper-diaries rely on user participation and are failing to provide objective information in times of asthmatic attacks. An alternative approach of continuous monitoring of patient’s environment and physiological functions has been reviewed. Unobtrusiveness and automated asthma management procedures exhibiting low interference with the daily routine of a patient are the key for a long-term adherence.

We focus our research on optimal design of a minimally intrusive body-worn wireless body sensor node for continuous monitoring of respiratory function. The battery operated node is working in conditions of limited energy and presence of background noise. The node features on-board signal processing and communicates with smartphone. Acquisition of respiratory sounds and signal processing focused on detection of wheezes and phases of respiratory cycle are the main features.

Main topics identified for further research include:

- frequency estimators for wheeze detection designed for operation on a energy constrained sensor node
- background noise cancellation
- node level and network level power management.

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