*Metrol. Meas. Syst.*, Vol. 30 (2023) No. 4, pp. 821–837
DOI: 10.24425/mms.2023.147956

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POLSKA AKADEMIA NAUK

METROLOGY AND MEASUREMENT SYSTEMS

Index 330930, ISSN 0860-8229
*www.metrology.wat.edu.pl*

# THREE METHODS FOR DETERMINING RESPIRATORY WAVES FROM ECG (PART I)

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**Abstract**

In the diagnosis of many disease entities directly or indirectly related to disorders of respiratory parameters and heart disease, an important support would be to estimate the temporal changes in these parameters (most often *respiratory wave* (RW) and *respiratory rate* (RR)) on the basis the results of measurements of other physiological parameters of the patient. Such a possibility exists during ECG examination. The paper presents three methods for estimating RW and RR using ECG signal processing. The three procedures developed are shown: using Savitzky–Golay filtering (S-G), the *ECG-Derived Respiration* method (EDR) and the *Respiratory Sinus Arrhythmia Analysis* method (RSA). It must be clearly stated that the proposed methods are not designed to fully diagnose the patient's respiratory function, but they can be applied to detect some conditions that are difficult to diagnose when performing an ECG, such as sleep-disordered breathing. The obtained results of the analysis were compared with those obtained from a dedicated measurement system developed by the authors. The second part of the paper will show the results of preliminary clinical verification of the developed analysis methods, taking into account the physiological parameters of the patient.

Keywords: respiratory rate, respiratory wave, ECG-derived respiration, respiratory sinus arrhythmia, Savitzky–Golay filtration.



## 1. Introduction

The *respiratory rate* (RR) constitutes a vital parameter that identifies the condition of human health [1]. The range of normal values for an adult at rest varies between 12 and 20 breaths per minute [2]. The selection of an appropriate measurement technique depends on the general condition of the examined patient and, especially, on the degree of contact. The most common



Article history: received July 7, 2023; revised August 28, 2023; accepted September 15, 2023; available online November 20, 2023.

technique for measuring the RR applies the use of a timer. It is listed among the group of non-contact methods as well as e.g. a technique that uses a depth sensing camera [3, 4]. Another group comprises direct contact methods and includes techniques based on the measurement of changes in the volume of the chest, humidity and temperature of the exhaled air, air flow and using electrocardiography, photoplethysmography or Doppler examination, as well as using Forcecardiography Sensors [5–16].

Measurement systems for recording and analyzing the respiratory signal are important in the proper diagnosis of respiratory diseases, especially in the detection of obstructive sleep apnea [17] and during electrocardiographic exercise testing [18, 19]. The article series [20, 21] describes selected physical and optical methods of respiratory diagnostics in otolaryngology. An interesting example is polysomnographic examination where, apart from respiratory activity, are recorded many other physiological signals *i.e. electrocardiography* (ECG), *electroencephalography* (EEG), *electrotrooculography* (EOG) or *electromyography* (EMG) [26]. The respiratory examination can also be analyzed using CT image processing. In the paper [28] there is presented a quantitative analysis of the results obtained from CT examination of the organs of the respiratory system [22].

As it was mentioned, obtaining information about respiratory activity from an ECG recording is of significant importance both in clinical practice and scientific research. From the clinical standpoint, during standard 24-hour Holter ECG monitoring, we can diagnose respiratory disorders, especially during the night, which plays a crucial role in determining the prognosis of patients with heart diseases [23]. Estimating respiratory disturbances based on Holter monitoring can also serve as a screening method in the diagnosis of sleep apnea [24]. In terms of scientific research, information about the respiratory waveform provides the opportunity to determine respiratory rate irregularities in the cardiac rhythm [25].

The techniques utilized for determining the RR based on ECG waveforms include such methods as: *amplitude modulation* (AM) [14,26], *frequency modulation* (FM) [27] and processing of *baseline wander* (BW) [11, 28]. The idea of obtaining the course of *respiratory waves* (RW) from the ECG using AM and FM modulation involves filtering of the upper frequencies of the signal, which form artifacts associated to the skeletal and respiratory muscles [29]. These two methods consider baseline wander as an unwanted low-frequency artifact. The third method – BW modulation forms an opposite approach as it does not cut-off low frequencies from the signal but applies filters for higher frequencies (greater than 0.5 Hz). In addition, it does not adversely affect the identification of respiratory waves during cardiac arrhythmias, unlike AM and FM modulations. Figure 1 shows the general characteristics of the mentioned methods.

In the processing with the *Baseline Wander* method (BW), the respiratory waveform (red line in Fig. 1 in the BW section) is derived from low-pass filtering of the ECG signal. In this case, the influence of electrical activity of skeletal and respiratory muscles on the ECG signal is used. In the case of modulation methods, the respiratory waveform information is contained in the differences in Q–R wave amplitudes and R–R intervals for AM (Fig. 1 AM section) and FM modulation (Fig. 1 FM section), respectively.

As a result of the application of an indirect manner of estimating the respiratory wave, based on ECG waveform processing methods, it is important to find a reference method to verify the results. Among the many methods that utilize different types of biosignals, a proposition has been made to apply a method for measuring changes in the chest circumference during respiration. This parameter can be measured by changing the pressure in an air-filled cuff located around the patient's chest. The key element enabling the measurement of gas pressure in the cuff is the pressure sensor. Sensors used in pressure measurements in biomedical devices are mainly based on piezoresistive sensors, in which the active measuring element takes the form

DOI: 10.24425/mms.2023.147956

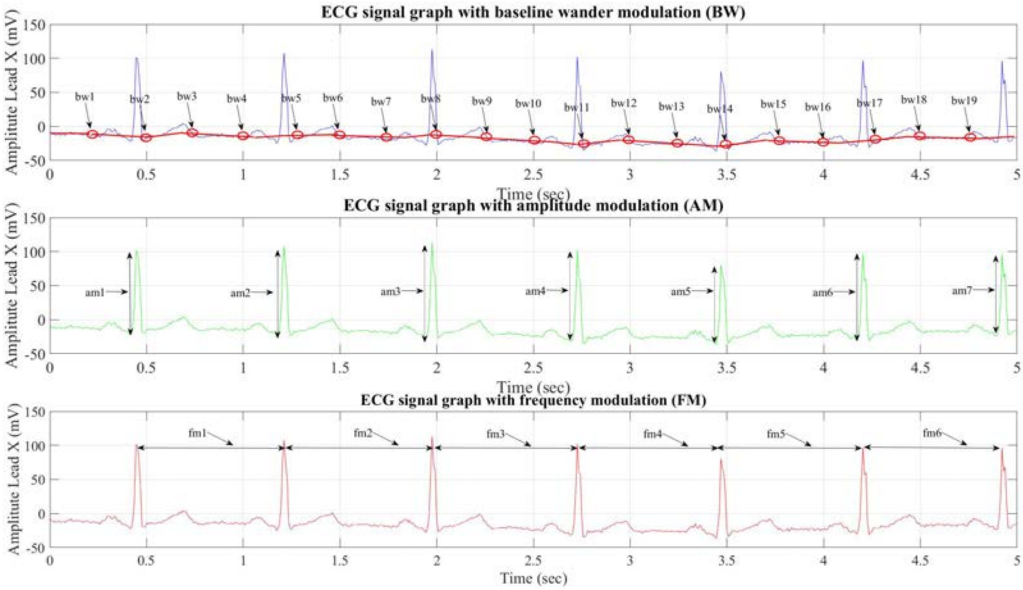


Fig. 1. Graphic interpretation of respiratory rate estimation techniques from ECG signal. Baseline wander modulation (BW), amplitude modulation (AM) and frequency modulation (FM). bw1, bw2, bw$_{n+1}$ denote successive values of the sampled signal after low-pass filtering. am2, am2, am$_{n+1}$ are the values of consecutive amplitudes of the Q–R amplitudes. fm1, fm2, fm$_{n+1}$ represent consecutive values of R–R intervals.

of a silicon membrane, interfacing with a resistance bridge, signal conditioners and an analog-to-digital converter. Two main concepts of this type of sensors can be distinguished: a discrete piezoelectric sensor interfacing with a separate electronic system and a monolithic pressure sensor containing both a membrane and an electronic system placed in one integrated circuit (a *Micro-Electromechanical System* (MEMS)).

The development of nanotechnology makes it possible to implement increasingly smaller measurement sensors, especially in the field of medical measurements. RR measurements can use ABPMAND001PG2A3 piezoresistive silicon pressure sensors, which can be placed in clothes or small pressure cuffs due to their dimensions of 8.1411.1419.23 mm. A prototype of the measurement system is shown in Fig. 2.

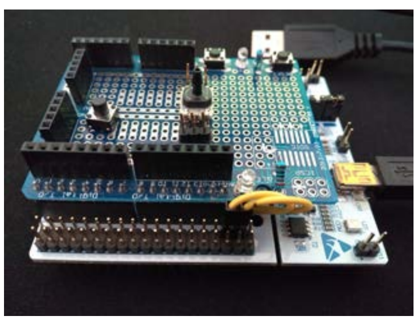

Fig. 2. Proprietary pressure measurement system using the MEMS system based on STM32 Microcontroller.

Measuring devices produced by application of the first of the mentioned technologies are characterized by larger dimensions, however, there is a greater potential for selecting the pressure transducers that are offered by various manufacturers and include a wide range of parameters. An example is an Aplisens PC-28 pressure sensor, which has an accuracy of 0.6%, compared to the exemplary MEMS ABPMAND001PG2A3 sensor, which is characterized by an accuracy of 1.5% [30].

This paper is the first of two which introduce three methods applicable for determining the RR and RW using the ECG signal: the BM method – *Savitzky–Golay* filtration (S-G), the AM method – *ECG-derived respiration* (EDR), and the FM method – *Respiratory Sinus Arrhythmia* (RSA). In particular, the S-G method finds unusual application in this case. The differences between the determined parameters of RW and RR for each method were presented. Moreover, the use of an embedded system with a high accuracy piezoresistive pressure sensor and a signal conditioning system as a combined reference device was shown. All the algorithms were implemented with the LabVIEW environment.

In the next paper, the results of research carried out on a group of patients, concerning different types of biomedical parameters, such as *Body Mass Index* (BMI), *Forced Expiratory Volume in 1 Second* (FEV1), *Forced Vital Capacity* (FVC) and *Tidal Volume* (TV) will be presented. In particular, the selection of optimal parameters of Savitzky–Golay filtering in the BW method is considered.

## 2. Methods for estimating respiratory wave and respiratory rate from ECG

The best-known methods for estimating RR from ECG signals are *ECG-derived respiration* (EDR) [31–33], *Respiratory Sinus Arrhythmia* (RSA) [11, 27, 35, 36, 38] and *Baseline Wander* (BW) modulation using the S-G filter [39–42]. The effectiveness of estimating RR for individual methods should be correlated with the reference signal coming from a specially designed respiratory recorder system [30, 43]. An important element of the examination is proper synchronization of the actual respiratory signal and the ECG signal.

### *2.1. Real time respiratory signal measurement using the designed embedded system*

The embedded system designed and developed by the authors was used as the reference system applied to record the respiratory wave and determine its frequency. It is shown in Fig. 3.

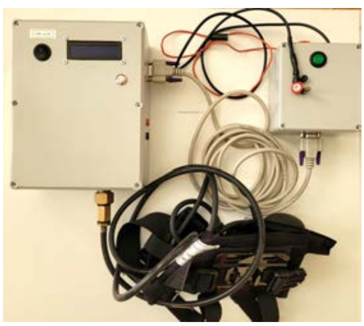

Fig. 3. Proprietary breath recording system using a piezoresistive sensor.

The device can also find application diagnosing respiratory diseases [18]. This device implements a microcontroller with low energy consumption. The system is based on an AVR Atmega328 microcontroller and is equipped with a 10-bit A/C converter [43]. The measurement system can record data at a user-selected signal sampling frequency. The study applied the tactile measurement method using a piezoresistive pressure sensor. The system includes a specially designed motherboard, a pressure transducer module, a shoulder strap with a cuff and the software implemented in LabVIEW. Due to the need to match the sampling frequency of the analog-to-digital converter of the ECG Holter and the respiratory recorder, it was set to 128 Hz. Initial cuff pressure was set so that it does not cause discomfort when breathing. In order to be able to visually interpret the inhalations and exhalations obtained during ECG signal processing, tests were conducted with forced breaths with momentary pauses between them. A block diagram of the program that extracts inspiration and RR from the measurement system is shown in Fig. 4.

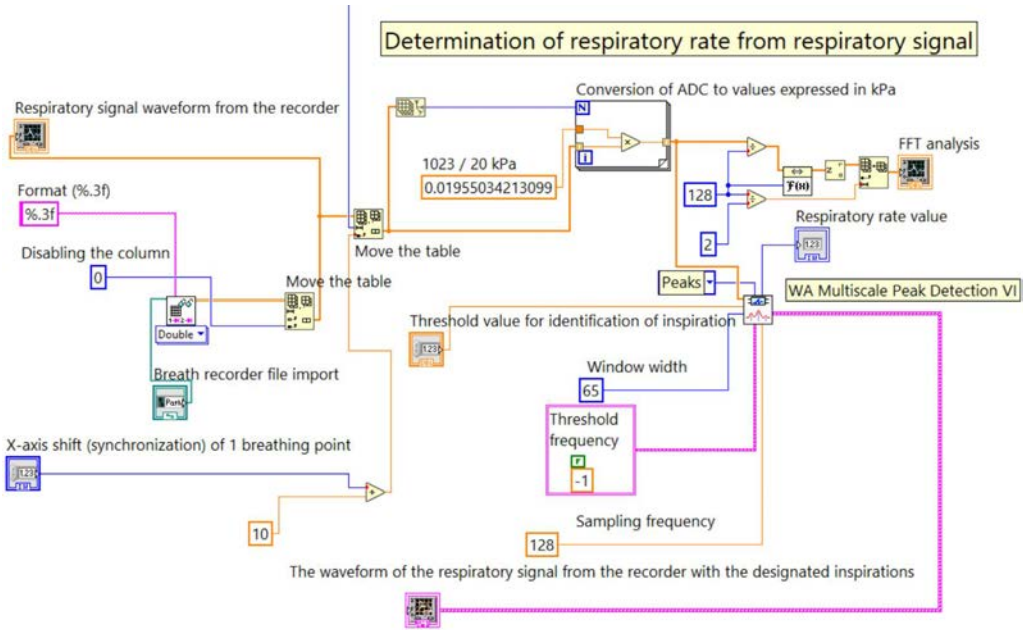


Fig. 4. View of the LabVIEW Block Diagram of the program that extracts inspiration and respiratory rate.

The software written by the authors allows changing the signal processing parameters and can be used by medical specialists due to its simple graphical interface. The device is completely safe and has been approved for medical experimentation in accordance with Resolution No. 319 of October 1, 2020 of the Bioethics Committee.

The algorithm for extracting the respiratory rate from a recorded respiratory wave by the reference embedded system consists of several steps. In the first step, a signal corresponding to changes in chest circumference is sampled at 128 Hz. It is then converted into pressure units – kPa. Due to the embedded system's 10-bit ADC and the piezoresistive sensor's pressure measurement range of 20 kPa, each sample is multiplied by a value 0.01955 (1023/20). Then a time waveform is created for which multiresolution wavelet analysis is performed using bior3_1 wavelet (WA Multiscale Peak Detection VI from the LabVIEW package). The threshold value is determined empirically and is usually half the value of the respiratory signal amplitude (between the minimum and maximum value of the signal amplitude). Due to possible faster breathing, the width of the window was set to the value of 65 (more than half a second) at a signal sampling frequency of 128 Hz. The a of the wavelet analysis is to obtain the values of peak amplitudes along with their location (sample numbers). The obtained data allow calculating the value of RR by dividing the number of determined peaks in the analysed signal by the time, set by the user.

### *2.2. ECG Holter monitoring*

The study applied a 12-lead Holter ECG device AsPEKT 812 v. 201 by ASPEL S.A. (Rev. 1.01). The sampling frequency of the signal is 128 Hz; hence this value is adopted in the built-in system applied for recording the RR.

The manufacturer's software HolCARD 24W allows export of data, including sample numbers with designated R-wave and R–R intervals. The measurement cycle starts with placing the ECG electrodes and attaching a chest strap from a breath recorder (Fig. 5).

Fig. 5. Holter ECG monitoring and respiratory signal measurement with the shoulder strap installed.

It is very important to synchronize the signals to be in phase with each other. The study was conducted at rest due to the best quality of the ECG and respiratory signal. A very important part of the measurement is the correct contact between the electrode and the skin [44].

### *2.3. Savitzky–Golay filtration*

As a result of filtering the upper frequencies of the ECG signal with an S-G filter, low-frequency artifacts related to respiratory muscle work are observed. It is noted that the changes in signal amplitude correlate with the breathing recorded from the measurement system. It was assumed that the length of the breathing cycle would be greater than half a second (fast breathing was omitted). The software developed in the LabVIEW environment can offer a choice of 12 ECG leads, duration analysis and initialization starting point (important for offline analysis). The block diagram of the designed program is shown in Fig. 6.

In this method, the data of vector $y$ are converted into the values of the $k$-th degree polynomial locally approximating the signal in the time window of width $f$, where each of the smoothed samples $y\_\{i\}$ occurs exactly in the middle of the window [45–47].

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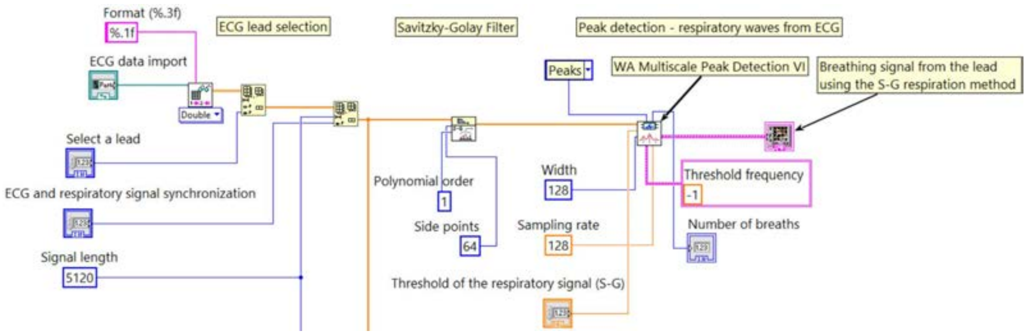


Fig. 6. View of the LabVIEW Block Diagram of respiratory waves estimation using S-G filtering.

Two parameters are assumed in this filter:

– width of the window with an odd value:

$$f = 2 \cdot m + 1, \tag{1}$$

where $m$ is the number of samples in the moving window,

– degree of polynomial $k$, where $f \gg k$.

RR estimation studies were carried out for various sets of S-G filtration parameters. It was empirically established that the filter parameters will be as follows: order of the polynomial: 1, side points 64 [30]. Wavelet analysis is widely used in ECG signal processing [48], thus the wavelet analysis implemented in the WA Multiscale Peak Detection VI module was used in order to identify inspirations in the processed ECG signal, (biorthogonal wavelet bior3_1). In the current version of the software, the respiration threshold is set manually.

The block diagram for determining the RR using the S-G method is shown in Fig. 7.

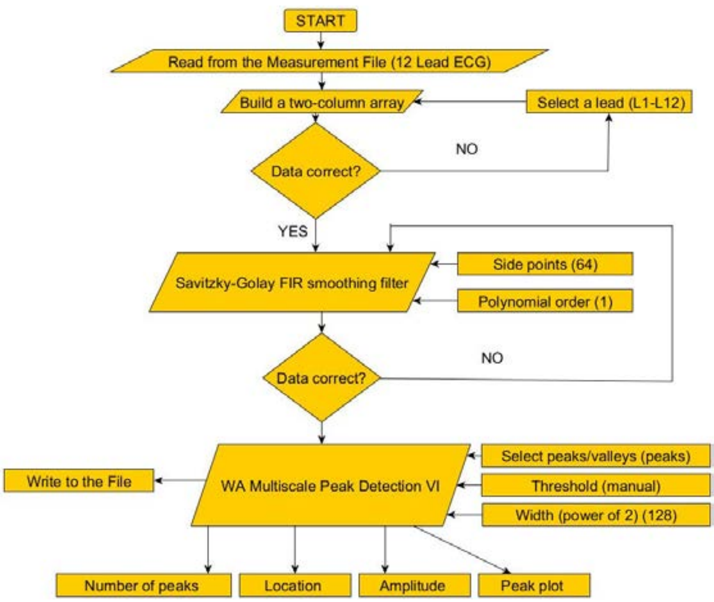


Fig. 7. Block diagram of RR determination for the method with S-G filtration.

As a result of the wavelet analysis, the obtained values such as file location and amplitude are written to the table. Based on the data, RR values are calculated over a user-specified time interval.

Processing the ECG signal to obtain the RW and RR is done in several steps. Initially, data from two files are loaded. One contains recorded data from a reference embedded system, and the other includes an ECG recording of 12 leads. Both signals are recorded with a signal sampling frequency of 128 Hz. The step of analysing the signal and obtaining the respiratory rate is presented in Section 2.1. In the case of ECG signal analysis, the user selects the number of the lead for which the signal will be analysed and sets the time of the analysed signal. In the next step, the two signals are synchronized with each other. Further, low-pass filtering is introduced using the Savitzky–Golay FIR smoothing filter. Filter parameters *i.e.* side points: 64 and polynomial order: 1 were selected based on the authors' research. For this set of filter's parameters, the smallest relative error in determining RR from the ECG signal was obtained. Next, multiresolution wavelet analysis was performed (as for the recorded respiratory signal, the value of the window width was selected individually, relative to the length of the analysed signal). The value of the respiratory rate is assumed to be no more than 30 breaths per minute. The sampling frequency of the signal was set to 128 Hz. The threshold for determining the peaks was set individually for each lead. The aim of wavelet analysis is to obtain the values of peaks of amplitudes along with their location. Ultimately, thanks to them, it is possible to create a RW and estimate the RR.

### 2.4. EDR method

The ECG-Derived Respiration method was proposed by George B. Moody from Massachusetts Institute of Technology [31]. The EDR technique is based on the dependence in which a change in the position of the ECG electrodes, and thus their position relative to the heart, affects changes in the amplitudes of the QRS complexes. The EDR algorithm implemented in the LabVIEW environment is presented in Fig. 8.

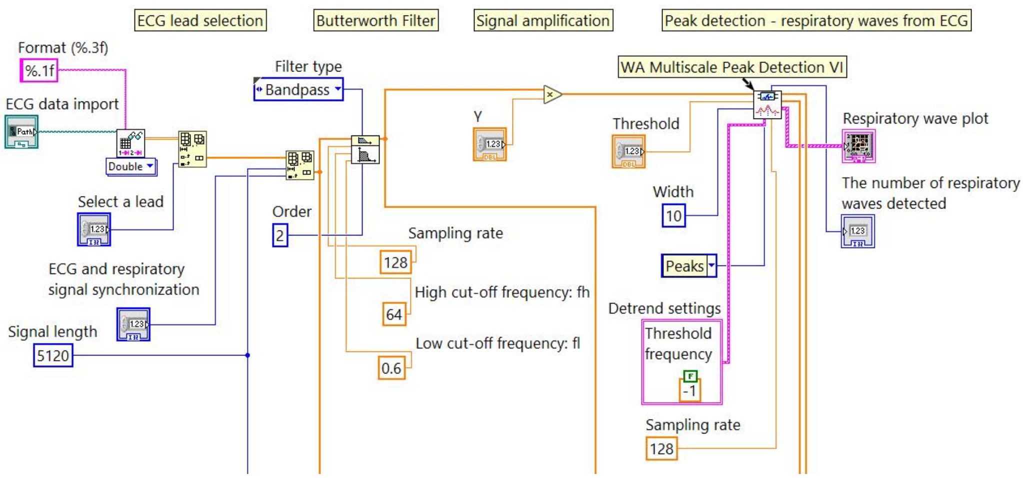


Fig. 8. View of the LabVIEW Block Diagram of respiratory waves estimating using the EDR and RSA methodology.

The block diagram of the EDR algorithm is shown in Fig. 9.

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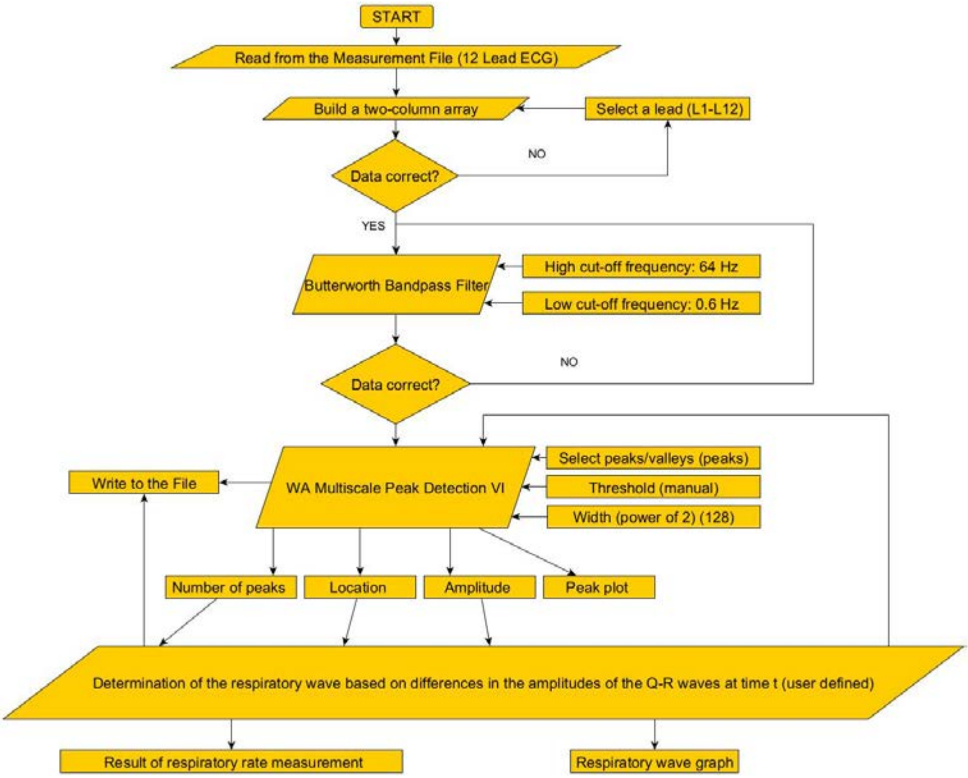


Fig. 9. Block diagram of RR determination for the EDR method.

The program can be used to select the ECG lead from which the respiratory signal is to be extracted with the chosen method and adopting its length. A Butterworth filter with a frequency response of 0.6 – 64 Hz was used to remove the baseline from the ECG signal. Q and R wave recognition is performed using the WA Multiscale Peak Detection tool in the LabVIEW environment. The results achieved with the method took the form of a 5-column table containing the amplitudes of the identified Q and R waves, their location and the difference of the Q and R amplitudes (the value adopted in the EDR method). A series of Q–R amplitudes provide the means to compile a respiratory waveform for a given lead (L1–L12) by interpolation. Fig. 10 shows the ECG record with local minima and maxima that form the respiratory wave.

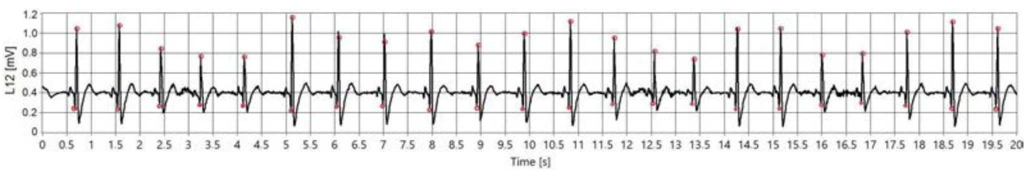


Fig. 10. Designated Q and R waves in the implemented EDR method algorithm.

Determining the RR from the ECG signal using the amplitude modulation method consists of several steps. As with the analysis of the ECG signal using the S-G technique, the user determines the number of the lead and the duration of the test. The signal is then passed through a band-pass Butterworth filter to remove the baseline. The cut-off frequencies of 0.6–64 Hz were adopted. In the next step, multiresolution wavelet analysis was performed to determine QRS bands. The threshold value for determining the peaks is set by the user individually to include only the QRS bands in the analysed ECG signal. The width of the window was empirically set at 20. The wavelet analysis yielded R-wave amplitude values along with their location. It was determined that the Q-wave is distant from the R-wave by 4 samples, hence it is possible to obtain a summary of Q–R amplitudes and their location. For the values obtained, a RW was created for which the wavelet analysis was again performed to determine RR values. It is important that the ECG signal does not have artifacts, because in the current version the software is not immune to signal distortion.

### 2.5. RSA method

The RSA method is based on *respiratory sinus arrhythmia* (RSA) and can be used to create a real time-domain respiratory waveform [37]. RR affects heart rhythm via the autonomic nervous system and a series of baro- and chemoreceptors in the circulatory system [36]. The block diagram of RR determination from the electrocardiogram signal by the RSA method is shown in Fig. 11.

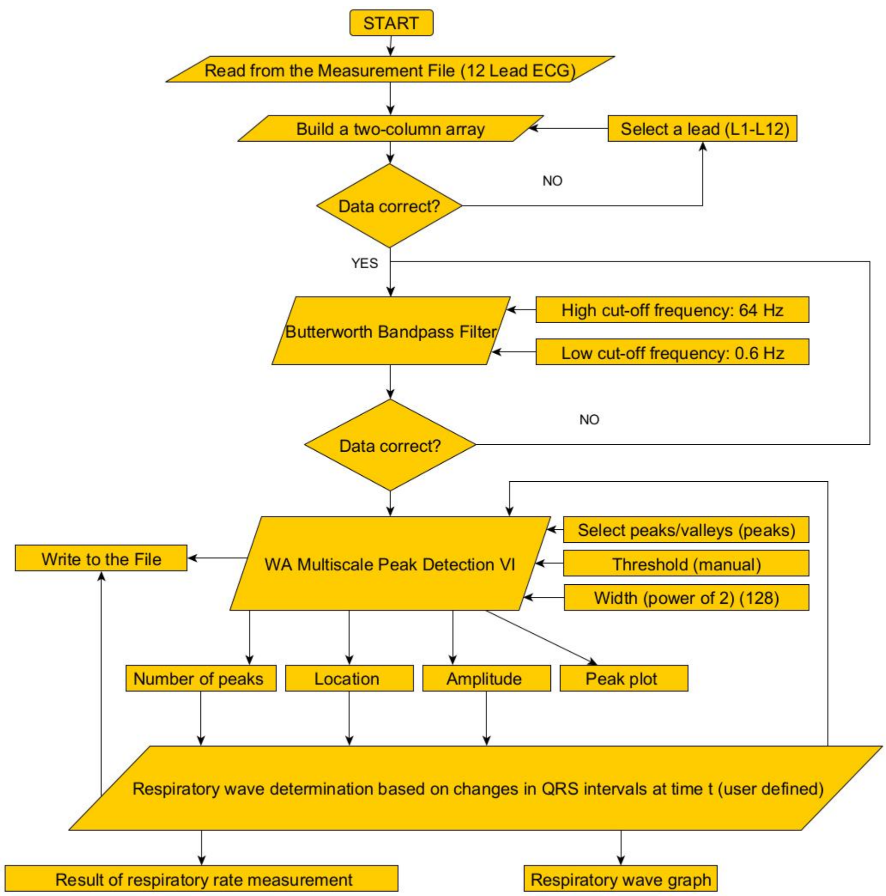


Fig. 11. Implemented RSA method algorithm.

Just as in the case of estimating the respiratory waves using the EDR method, the ECG signal for RSA is subjected to the filtration with a Butterworth band-pass filter (0.6 – 64 [Hz]) to remove ECG Base Wander from the ECG signal. The Multiscale tool was also used in the Peak Detection Method to determine the peaks of the QRS complexes. The results of the block operation take the form of the obtained values of the R-wave amplitude and their positions in the table (signal sample number). The RSA method is based on the same algorithm for determining respiratory waves as in the case of the EDR method, however, the R–R intervals are used in the place of the values of the amplitudes of the Q–R waves. A time series of R–R intervals creates a respiratory waveform for a particular lead. On the basis of the regenerated data gained with regard to the R–R intervals, a respiratory wave graph was developed. It is important that the threshold value for determining the peaks is determined individually.

The algorithm for determining the RR from the ECG signal using the frequency modulation method consists of the same steps as the EDR algorithm. The difference lies in the way of obtaining the RW (using wavelet analysis) from a set of data: the R–R interval and the sample number. Running the wavelet analysis again to determine the number of peaks in the analysed duration allows the calculation of RR values.

## 3. Comparison of the methods

The result of running the LabVIEW application is the acquisition of respiratory waveforms from the ECG signal for each method (S-G, EDR and RSA) and the estimation of the respiratory rate. Fig. 12 shows inspiratory breaths, which also represents an increase in the subject's cuff pressure. The pressure is correlated with the rise and fall of the chest, which makes it possible to estimate the shape of the respiratory waveform. Respiratory waveforms obtained from each methods: S-G, EDR and RSA are shown in the individual Figures: 13, 14, 15, respectively.

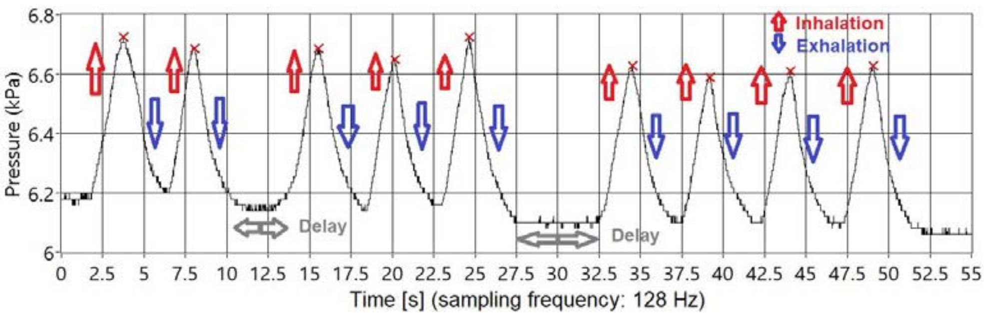


Fig. 12. Plots of the respiration signal with marked inhalations and exhalations.

Algorithms for determining RR from ECG signal were tested for a man aged 68 years. This is the example of the results obtained, which will be presented more extensively in Part II of the publication. The test consisted of simultaneous recording of the respiratory signal using a proprietary embedded measurement system and a 12-lead Holter ECG. S-G filtering parameters were chosen empirically and are as follows: filter order: 1, window width 64.

It is possible to obtain the shape of the respiratory waveform for all methods. The S-G method reflects the respiratory waveform to the greatest extent due to the largest number of samples among the methods tested. This number is equal to the number of samples of the input ECG signal. For

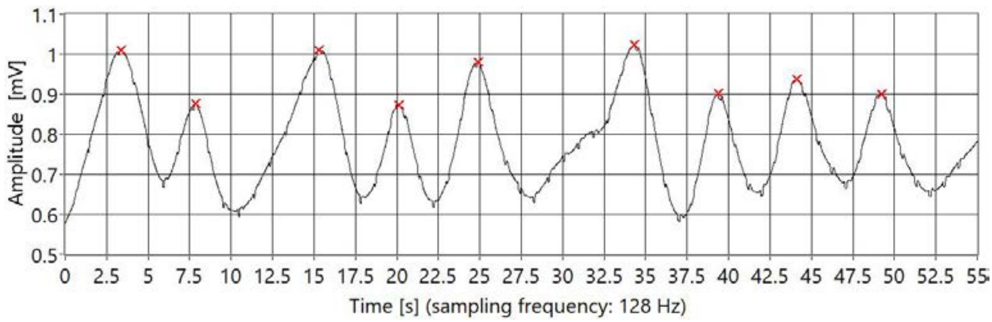


Fig. 13. Plots of the respiration waves with marked exhalations for the method with S-G filtration.

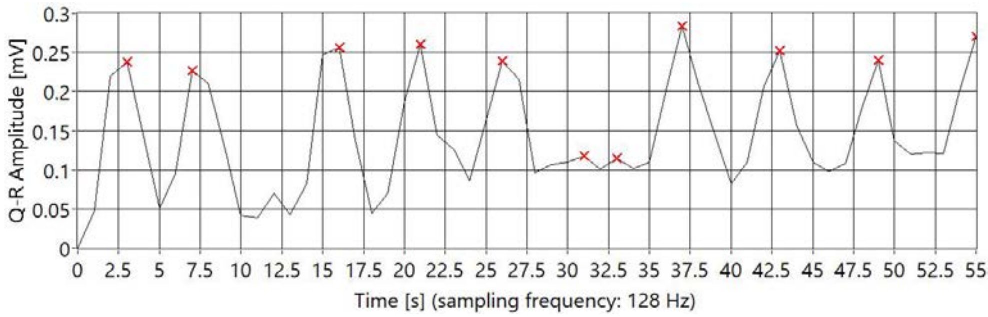


Fig. 14. Plots of the respiration waves with marked exhalations for the EDR method.

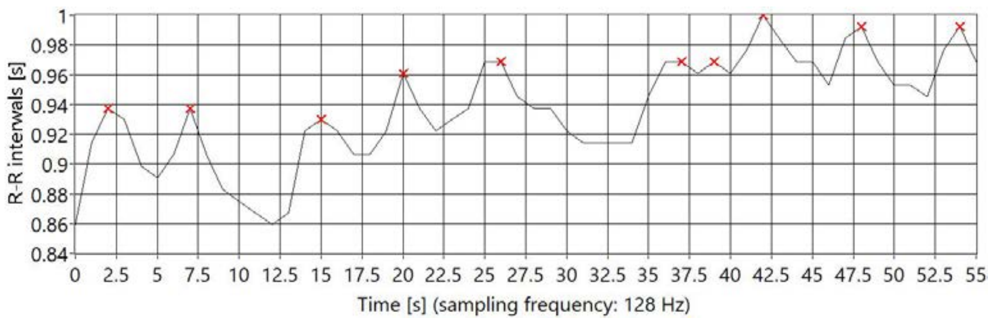


Fig. 15. Plots of the respiration waves with marked breathing exhalations for the RSA method.

the EDR and RSA methods, the number of samples of the obtained respiratory waveform is equal to the number of specific R-waves in the ECG signal.

The results obtained with the S-G method are more informative because of the ability to observe the exact shape of the respiratory waveform. Either method can determine the RR based on the detection of local maxima. In contrast, the smallest difference between local maxima occurs with the RSA method, which may carry the risk of erroneously detecting additional breaths. However, in the case studied, EDR erroneously detected breaths at time points of 30 and 32.5 [s] and 55 [s].

The advantage of using the EDR and RSA methods is that respiratory waveforms can be obtained independently from each lead since the Q–R waveforms and R–R intervals are the same for each lead. However, it should be noted that artifacts in the ECG signal can appear in different leads. In these methods, it is more important to correctly identify all QRS complexes.

A feature of the S-G method seems to be the strong dependence of the estimated respiratory waveform on the ECG lead number. This is due to different effects of skeletal muscle on the amplitude of the ECG signal for each lead. For this reason, it is particularly important to study the influence of physiological parameters such as BMI and functional respiratory capacity. To determine which method more accurately estimates waveform and RR, studies involving 12 ECG leads for people with different physical parameters are needed. Undoubtedly, this approach is novel and there is no currently research that defines the relationship of determining RR for different individuals.

## 4. Conclusions

This paper is the first part of a publication on *respiratory waveform* (RW) and *respiratory rate* (RR) estimation based on ECG signal processing. An algorithm using baseline wander analysis (Savitzky–Golay filtering) and algorithms based on amplitude modulation (EDR) and frequency modulation (RSA) of the ECG signal were investigated. The determined parameter RRs were compared to a reference signal obtained from an author's embedded measurement system. The system records pressure changes in the cuff surrounding the chest during breathing. It works with an application that allowed data acquisition and implementation of individual algorithms in the LabVIEW environment.

The use of S-G filtering in respiratory waveform RW estimation is unusual, and the study shows that it is possible to create it while obtaining a larger number of samples in the time domain, compared to EDR and RSA analyses. This feature may carry potential additional diagnostic features in diagnosing heart and lung diseases. Based on the results obtained, the characteristics of each method were determined.

It was concluded that further research is needed that take into account a study group differentiated by physiological parameters such as BMI and functional parameters of the respiratory system, which will be presented in the second part of this publication. Finally, the investigated analyses can serve as auxiliary methods for diagnosing respiratory diseases and heart diseases.

### Acknowledgements

The authors acknowledge the support that they have received from the Opole University of Technology for using ECG Holter. The study was conducted in accordance with Resolution No. 319 of October 1, 2020 of the Bioethics Committee authorizing the conduct of a medical experiment for implementation.

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