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THREE METHODS FOR DETERMINING THE RESPIRATORY WAVES FROM ECG (PART II)

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Abstract

This paper presents the results of a study of three methods for estimating the respiratory wave (RW) and respiratory rate (RR) using the electrocardiogram (ECG). There were applied methods from different groups: amplitude modulation ECG-Derived Respiration (EDR), frequency modulation Respiratory Sinus Arrhythmia (RSA) and Baseline Wander (BW) processing with the Savitzky-Golay filter (S-G). The theoretical aspects of the methods were presented in the Part 1 of the publication which was entitled: "Three Methods for the Determination of the Respiratory Waves from ECG Part I". RR parameter estimation was performed for all the three methods for 12 subjects. The research concerning the influence of the parameters: Body Mass Index (BMI), Tidal Volume (TV) - , Forced Expiratory Volume in 1 second (FEV1) and - Forced Vital Capacity (FVC) on the errors of the estimated parameter RR. Moreover, all 12 signals, which were acquired with the help of a 12-lead Holter ECG were taken into consideration. The results indicate a preliminary dependence of respiratory parameters and BMI on the Respiratory Wave and, further, on the RR estimation errors. Consequently, the type of method and ECG Holter leads depend on the BMI and respiratory parameters. Studies with larger numbers of objects to definitively confirm these relationships are planned. In addition, an optimal selection of S-G filter parameters was carried out. Finally, a proprietary reference embedded system for recording RW and calculating RR was demonstrated.

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

1. Introduction

One of the important parameters used in cardiac diagnostics is *respiratory rate* (RR). Typically, ECG recording devices (e.g., Holter ECG) do not monitor this parameter. Additional devices are used for this purpose. However, it has been noted that it is possible to obtain information on the chest movement from the ECG waveform itself. This makes it possible to determine the respiratory waveform RW, from which the parameter RR is estimated.

Estimating RR from electrocardiographic signal was pioneered by George B. Moody of the Massachusetts Institute of Technology [1, 2]. Although Professor Moody died as a result of the Covid'19 disease in 2021, he left behind a tremendous legacy related to electrocardiographic signal processing having co-founded the freely available biomedical data library PhysioBank [3]. Currently under development are also the George B. Moody PhysioNet Challenges, where new algorithms are being developed for medical purposes. In addition, an artificial medical intelligence research foundation is being established and a collaboration between Google Health and PhysioNet has been formed.

There are many methods for estimating the RR parameter from ECG waveforms. They can be divided into the following groups: *amplitude modulation* methods (AM), *frequency*

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modulation methods (FM) and *baseline wander* modulation methods (BM). These methods make it possible to create a *respiratory wave* (RW). In the last method, unlike the others, the breathing wave is obtained by low-pass filtering. Because such an RW carries the effects of skeletal muscle activity, it is a more accurate representation of the effect of chest rise. Analysis of such a signal, in addition to estimating the RR parameter, can provide additional diagnostic information.

The cardiovascular system is closely linked to the respiratory system [4, 5]. Diagnostics of respiratory processes are very important for both the respiratory and cardiac systems [6–13]. The study of the relationship between respiratory parameters obtained from spirometry, *body mass index* (BMI) and the error in determining RR from the ECG signal is a novel approach. Respiratory parameters recorded during the spirometry examinations reflect disorders in the respiratory system that result in changes in the dynamics of RR and, in particular, in the frequency and amplitude of respiration. The most frequently marked parameters include: *functional residual capacity* (FRC), *expiratory reserve volume* (ERV), *forced expiratory reserve volume in 1sec* (FEV1) and *total lung capacity* (TLC). In addition to respiratory diseases, the dynamics of breathing is also affected by obesity, which is determined on the basis of body mass index (BMI) [14–17]. Impairment of the respiratory function is associated with fat deposits on the diaphragm, abdomen and intercostal muscles. Obesity is a significant factor associated with respiratory disorders, particularly obstructive sleep apnea and *obesity hypoventilation syndrome* (OHS). The condition affects outcomes in *acute respiratory distress syndrome* (ARDS) and *chronic obstructive pulmonary disease* (COPD). (An analysis of the influence of the BMI parameter (in addition to age and gender) on the measurement of RR appeared in the 2021 publication by Aravind Natarajan [18]). For this reason, there is a high probability that a relationship between BMI and respiratory disorders (as represented by spirometry parameters) affects the accuracy of determining RW from electrocardiogram signal.

The publication aims to present and compare the ability to create RW and evaluate the estimation errors of the RR parameter obtained using three methods, which are representative of the AM method - *ECG-Derived Respiration* (EDR), the FM method - *Respiratory Sinus Arrhythmia* (RSA) and BW method. The last method used Savitzky-Golay filtering (S-G), which is typically used to improve the signal-to-noise ratio in ECG signals. In the authors' approach, it was used to separate the baseline wander and consequently determine the respiratory waveform RW. This approach is a new solution, in which a waveform with a larger number of samples is obtained, which can, compared to other methods, increase the diagnostic value of the method. In addition, a proprietary embedded system, using pressure measurement, in a cuff surrounding the chest, was used as a reference device to verify the results obtained.

The theoretical aspects of the issues were presented in the first part of the publication, in the paper entitled: “Three Methods for Determining the Respiratory Waves from the ECG (part I)” [19]. In the current, second part, the selection of optimal S-G filter parameters to enable baseline wander extraction from the ECG signal will be carried out, and the effect of ECG lead number selection on RR estimation error for each method will be investigated. In addition, a study will be undertaken to answer the question of whether physiological parameters: BMI and respiratory parameters (TV, FEV1 and FVC) affect the RR estimation error of each analysis.

2. Respiratory parameters TV, FEV1 and FVC

Tidal volume is the amount of air that moves in or out of the lungs with each respiratory cycle. Normally, this value is about 500 ml and depends on the size of the individual and its metabolic status [20]. An example of a spirometry test with basic lung parameters is presented in Fig. 1 [21].

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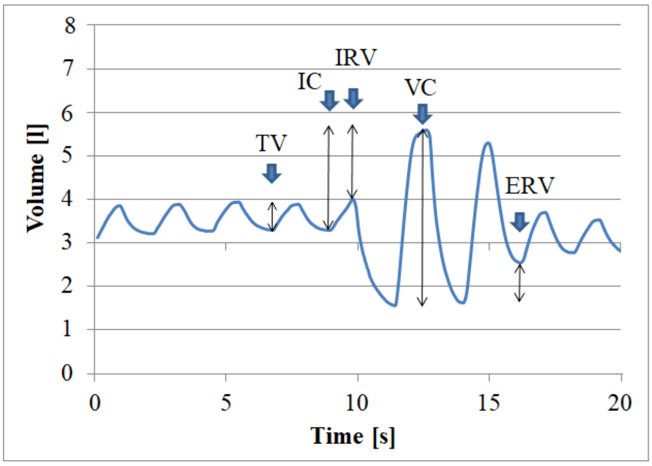

Fig. 1. Graph showing recorded changes in lung volume during a spirometry test. Tidal Volume (TV); Inspiratory Capacity (IC); Inspiratory Reserve Volume (IRV); Vital Capacity (VC); Expiratory Reserve Volume (ERV).

Spirometry also offers two more respiratory parameters: FEV1 and FVC [22, 23]. FEV1 is the volume of air that the patient is capable of exhaling from in one second of forced exhalation. This parameter depends on the volume of the lungs. The FVC parameter determines the total amount of air that the subject can exhale from the deepest inhalation to the maximum exhalation.

TV, FEV1 and FVC parameters were measured for all subjects using a Spirobank II by MIR. Subsequently, the influence of the resulting parameters on the determination of respiratory waves and respiratory rates from the ECG signal was analysed.

3. Research methodology

3.1. Participants

The study was carried out on a group of 12 apparently healthy subjects in the age between 25 and 69 years. The research protocol was approved by the local Ethics Committee and the study was conducted in accordance with the Declaration of Helsinki. The research carried out and its statistical analysis is a continuation of the research by our research group on the processing of biomedical signals [24, 25]. The scope of the study included recording breathing at rest and ECG testing using a 12-lead Holter ECG. Respiratory wave plots were recorded by the reference device when subjects were in the sitting position. The initial stage of examination included the measurement of the *Body Mass Index* (BMI) and a spirometry test, the result of which took the form of the registration of the following parameters: FEV1 (*Forced Expiratory Volume in 1 second*), FVC (*Forced Vital Capacity*) and TV (*Tidal Volume*). Table 1 contains a summary of the results of spirometry tests for individual subjects.

The BMI ranges offered the classification of subjects into 3 groups: 18-20 (underweight), 20.1-25 (normal weight) and 25.1-35 (overweight and obese). For TV, it measures around 500 ml in an average healthy adult male and approximately 400 ml in a healthy female. However, the achieved values of TV parameters are higher than expected. This is most likely caused by taking measurements of respiratory parameters after recording ECG signals, during which the subjects performed specific breathing series.

Table 1. Subjects of the study.

Subject	Gender	Age	BMI	Number of breaths	FEV1 [l] / (%pred)	FVC [l] / (%pred)	Tidal Volume (l)
6	F	25	18.03	21	3.28 / (111)	3.57 / (105)	1.11
10	M	30	18.52	16	5.41 / (118)	6.74 / (122)	0.98
2	F	36	19.61	32	3.78 / (118)	4.34 / (113)	0.52
5	M	36	20.52	23	4.43 / (118)	4.71 / (104)	1.09
9	M	29	22.64	19	5.03 / (106)	6.43 / (113)	1.68
7	F	61	24.80	15	3.01 / (122)	3.74 / (122)	1.28
11	F	29	25.65	14	4.86 / (147)	5.09 / (130)	1.7
8	M	68	26.58	21	4.07 / (109)	5.67 / (120)	1.48
12	M	32	27.08	16	6.64 / (161)	7.27 / (147)	1.96
1	M	45	29.22	26	4.63 / (104)	5.34 / (97)	1.41
3	M	33	29.35	34	4.4 / (102)	6.92 / (132)	1.24
4	M	41	32.11	28	4.29 / (119)	4.44 / (110)	1.2

3.2. Measurement laboratory stand

The laboratory stand includes: an AsPEKT 812 v. 201 - Holter ECG by ASPEL S.A, a spirometer - Spirobank II by MIR (software version 2.5), a proprietary reference embedded respiratory waveform recorder system, and a PC computer with the LabVIEW environment. Fig. 2 shows the laboratory stand.

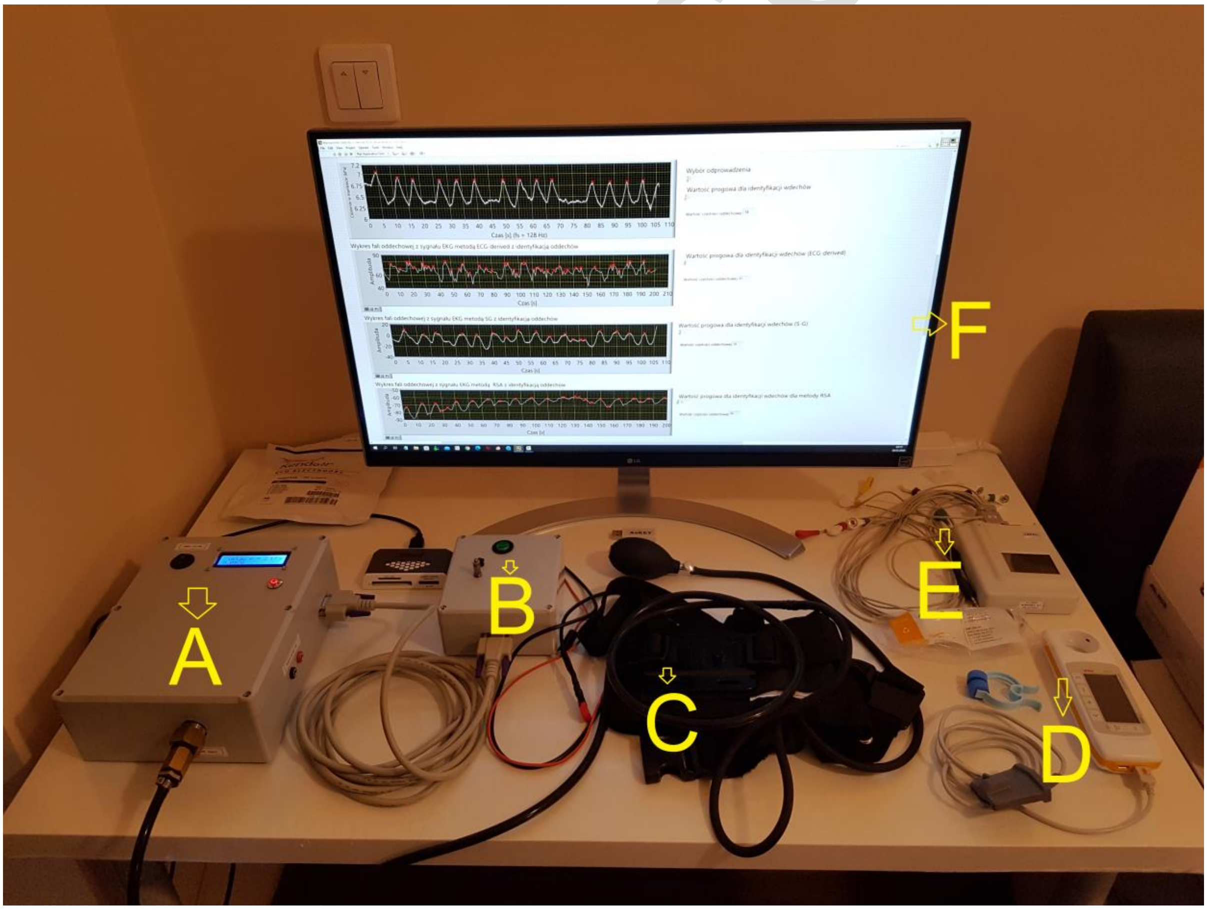

Fig. 2. Laboratory stand for recording the respiratory waveform, ECG and spirometry tests (A: reference embedded system for recording the respiratory waveform, B: synchronization system for Holter ECG and reference embedded system, C: chest pressure cuff of the reference embedded system, D: spirometer, E: Holter ECG, F: computer with the LabVIEW environment).

The main parameters of the Holter ECG:
- number of leads: 12,
- analog-to-digital converter resolution: 16 bits,
- sampling rate: 128 Hz,
- frequency response: 0.05 Hz – 80 Hz,
- input impedance: > 10 MΩ,
- common mode rejection ratio CMRR: >80 dB.

The reference embedded system for recording respiratory waveforms, using the measurement of the pressure of the cuff surrounding the chest, allows recording of the signal with a resolution of 10 bits and a user-settable sampling rate (standard: 128 Hz). The technical data of the PC-28 pressure sensor installed in reference embedded system for recording respiratory waveform are as follows:
- accuracy: 0.3 %,
- thermal error: typically 0.3% / 10°C; max 0.4% / 10°C,
- hysteresis, repeatability: 0.05%,
- response time < 120 ms,
- output signal 4...20 mA,
- error due to supply voltage changes 0.005%/ V,
- damaging overpressure: 200 kPa.

The ECG and respiratory waveform signal synchronizer allow temporal synchronization of signals obtained from the reference embedded system and the ECG Holter with an accuracy of 1 sample.

The spirometer used allows for respiratory function tests, including TV, FEV1, and FVC parameters, taking into account factors such as age, sex, weight, height, and race/ethnicity [22]. The main features of the MIR Spirobank II Advanced spirometer are presented below:
- flow sensor bi-directional digital turbine,
- volume accuracy ±2.5% or 50 ml,
- flow range ±16l/s,
- flow accuracy ±5% or 200 ml/s,
- dynamic resistance <0.5 cm H2O/l/s.

The laboratory workstation is also equipped with a PC with the LabVIEW environment and additional modules installed: Digital Signal Processing and Biomedical Toolkit. Data exchange between the reference embedded system and the computer is carried out using an RS232/USB terminal, allowing time-sensitive recording.

3.3. Measurement procedure

The following measurement procedure has been implemented:
- spirometry examination and calculating of following parameters of each subject: BMI, TV, FEV1, FVC [26],
- respiratory waveform and ECG recordings for each subject:
  - connecting of a reference embedded system for WR and RR registration,
  - connecting of 12-lead Holter ECG,
  - beginning of recording using a reference embedded system and a Holter ECG,
  - performing a specific breathing cycle, consisting of a series of inhalations and exhalations (details in Part I of the publication),
- post-processing in the LabVIEW environment of signals obtained from:
  - a reference embedded system,
  - a Holter ECG with implementation of (for each of 12 leads): S-G filtration, EDR, RSA method.

4. Research results

4.1. Determination of the measurement error

The correlation between reference and extracted respiratory signal was performed. The quality criteria of the method are related to relative measurement error *Re* [24].

The relative error *Re* was calculated to the following equation:

$$Re = \frac{|Vme - Vre| \cdot 100\ [\%]}{Vre}, \tag{1}$$

where:

Re – relative error [%],
Vme – measured value of RR,
Vre – real value of RR.

The results of the tests conducted to determine the number of breaths with the methods: S-G, EDR and RSA are presented in Tables 4, 5, 6 respectively. The tables show the breath detection results for each of the 12 patients during the 106 second measurement sessions.

4.2. Testing Savitzky-Golay filter parameters

For S-G filtration, the results of estimating local extremes using wavelet analysis (biorthogonal wavelet bior3_1) for various filter settings are summarized and presented in Table 2.

Table 2. Results for detection of local extremes in V6 ECG lead for 9 breaths with variable S-G filter parameters.

Number	Polynomial order	Side points	Number of detected local extremes (breaths)	Number of incorrectly detected breaths
1	1	1	9	2
2	1	2	9	2
3	1	4	9	2
4	1	16	10	1
5	1	32	9	1
6	1	64	9	0
7	1	128	7	2
8	1	256	5	4
9	2	1	9	2
10	2	2	9	2
11	2	4	9	2
12	2	16	9	2
13	2	32	10	1
14	2	64	9	2
15	2	128	9	0
16	2	256	7	2
17	3	2	9	2
18	3	4	9	2
19	3	16	9	2
20	3	32	10	1
21	3	64	9	2
22	3	128	9	0
23	3	256	6	3

A conclusion was made on the basis of the results of breath detection from the ECG signal for different S-G filter settings that the three various settings offered correct results. Therefore, another measurement of RR was performed. The results of breath detection are shown in Table 3.

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Table 3. Results for detection of local extremes in V6 ECG lead for 6 breaths with variable S-G filter parameters

Number	Polynomial order	Side points	Number of detected local extremes (breaths)	Number of incorrectly detected breaths
1	1	64	6	0
2	2	128	7	1
3	1	4	7	1

The largest number of detected breaths from the ECG signal was determined in the case of S-G filtration: side points 64 and polynomial order 1. Therefore, all respiratory rate waveform analyses will be performed for these filter settings. In addition, the computational complexity is the least for this order.

4.3. Results for the S-G, EDR and RSA methods

The small number of subjects included in the study prevented the researchers from executing a comprehensive statistical analysis based on the probability distribution along with the presentation of hypotheses. Therefore, the S-G, EDR, and RSA methods were compared in terms of median relative error for each lead. Table 4, Table 5 and Table 6 show, respectively, the results of calculations of the RR error expressed by (3) for: S-G, EDR and RSA methods, taking into account each of the 12 leads that provided ECG inputs. The number of breaths for each subject in a given test was different, therefore, the relative error was adopted as the outcome of the effectiveness of estimating the number of breaths in relation to the measurement made by the RR recorder. For leads I, II, III, aVL, aVR, aVL, V1 to V6, the numbering of L1 to L12 was adopted, respectively. Table 7 contains a summary of the median, mean, and standard deviation values for all subjects for leads L1-L12.

Table 4. Results for relative errors in respiratory waves designating using S-G filtration.

Subject	Relative error [%] using S-G filtration Number of the ECG lead:											
	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
1	19.23	38.46	42.31	46.15	61.54	26.92	50.00	57.69	42.31	46.15	11.54	34.62
2	62.50	46.88	46.88	62.50	46.88	50.00	53.13	68.75	40.63	50.00	46.88	37.50
3	29.41	29.41	38.24	35.29	35.29	32.35	50.00	44.12	44.12	38.24	41.18	41.18
4	25.00	14.29	14.29	21.43	25.00	10.71	42.86	14.29	14.29	32.14	28.57	0.00
5	34.78	13.04	17.39	13.04	8.70	17.39	17.39	52.17	13.04	13.04	17.39	17.39
6	14.29	19.05	14.29	23.81	4.76	19.05	14.29	0.00	14.29	9.52	23.81	9.52
7	53.33	26.67	26.67	0.00	6.67	26.67	33.33	40.00	53.33	6.67	0.00	6.67
8	28.57	14.29	23.81	19.05	14.29	19.05	14.29	19.05	14.29	4.76	19.05	19.05
9	5.26	5.26	5.26	10.53	5.26	5.26	0.00	5.26	5.26	0.00	10.53	10.53
10	12.50	12.50	12.50	6.25	18.75	12.50	18.75	18.75	18.75	12.50	31.25	43.75
11	14.29	7.14	14.29	0.00	7.14	14.29	0.00	21.43	14.29	0.00	7.14	21.43
12	25.00	12.50	31.25	12.50	31.25	25.00	18.75	12.50	18.75	6.25	6.25	6.25

Table 5. Results for relative errors in respiratory waves designating using the EDR method.

Subject	Relative error [%] using the ECG-derived respiration method Number of the ECG lead:											
	L1	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**	**L9**	**L10**	**L11**	**L12**
1	3.85	50.00	26.92	15.38	19.23	26.92	3.85	3.85	0.00	46.15	11.54	19.23
2	3.13	3.13	3.13	3.13	3.13	3.13	3.13	3.13	3.13	3.13	3.13	3.13
3	5.88	2.94	2.94	14.71	97.06	11.76	2.94	5.88	8.82	2.94	8.82	8.82
4	17.86	14.29	17.86	7.14	17.86	14.29	25.00	32.14	14.29	25.00	39.29	17.86
5	0.00	17.39	30.43	21.74	26.09	43.48	34.78	17.39	17.39	26.09	26.09	26.09
6	14.29	61.90	38.10	57.14	33.33	38.10	0.00	19.05	9.52	23.81	9.52	4.76
7	6.67	20.00	120.00	66.67	100.00	273.33	73.33	33.33	93.33	353.33	166.67	6.67
8	66.67	28.57	28.57	47.62	38.10	19.05	23.81	38.10	0.00	23.81	0.00	4.76
9	26.32	31.58	36.84	21.05	63.16	26.32	63.16	63.16	47.37	10.53	15.79	10.53
10	106.25	87.50	93.75	81.25	112.50	93.75	75.00	75.00	68.75	50.00	62.50	62.50
11	21.43	164.29	200.00	157.14	142.86	150.00	121.43	92.86	100.00	100.00	85.71	192.86
12	206.25	237.50	225.00	212.50	175.00	225.00	168.75	37.50	18.75	187.50	250.00	212.50

Table 6. Results for relative errors in respiratory waves designating using the RSA method.

Subject	Relative error [%] using the RSA-derived respiration method Number of the ECG lead:											
	L1	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**	**L9**	**L10**	**L11**	**L12**
1	15.38	23.08	19.23	11.54	7.69	11.54	19.23	15.38	23.08	19.23	23.08	3.85
2	6.25	3.13	3.13	3.13	0.00	3.13	3.13	3.13	3.13	6.25	3.13	12.50
3	29.41	26.47	26.47	26.47	41.18	26.47	26.47	26.47	26.47	29.41	32.35	23.53
4	50.00	17.86	10.71	7.14	3.57	17.86	0.00	7.14	7.14	3.57	3.57	21.43
5	4.35	8.70	8.70	8.70	8.70	8.70	8.70	8.70	8.70	8.70	8.70	4.35
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	40.00	33.33	126.67	40.00	53.33	53.33	33.33	40.00	26.67	33.33	33.33	20.00
8	14.29	9.52	14.29	14.29	9.52	9.52	4.76	14.29	14.29	14.29	14.29	9.52
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	81.25	12.50	12.50	12.50	12.50	12.50	6.25	12.50	12.50	0.00	12.50	12.50
11	7.14	7.14	7.14	7.14	14.29	7.14	7.14	14.29	7.14	7.14	7.14	14.29
12	81.25	56.25	56.25	93.75	62.50	56.25	56.25	68.75	100.00	68.75	56.25	156.25

Table 7. Results for mean and median calculation of relative errors for the three methods.

	S-G filtration			EDR method			RSA method		
Number of the ECG lead	**Median [%]**	**Mean [%]**	**SD [%]**	**Median [%]**	**Mean [%]**	**SD [%]**	**Median [%]**	**Mean [%]**	**SD [%]**
L1	26.79	28.49	17.98	16.73	23.05	37.03	14.84	24.09	26.37
L2	16.67	21.98	13.1	21.24	28.04	20.43	11.01	13.46	11.47
L3	20.60	24.16	14.08	24.81	28.06	18.63	11.61	22.17	37.65
L4	20.24	23.81	19.22	25.45	32.18	26.79	10.12	12.38	12.47
L5	16.52	22.71	19.5	18.76	20.87	16.57	8.19	13.65	18.47
L6	19.05	21.99	12.8	17.19	24.36	27.64	10.53	14.30	15.93
L7	26.04	29.40	18.82	1.56	8.04	12.47	5.51	10.19	11.98
L8	29.52	32.01	23.63	12.22	19.64	21.83	10.60	12.76	12.5
L9	16.52	26.03	17.05	12.58	20.03	20.13	10.60	12.20	10.29
L10	12.77	21.30	18.47	14.50	23.31	17.66	7.47	11.48	12.29
L11	21.43	23.02	14.39	14.29	18.07	12.82	10.60	13.09	12.62
L12	18.22	22.02	15.9	19.82	23.79	17.73	11.01	10.77	8.76

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5. Discussion

5.1. Research of effectiveness of determination of ECG signal derived respiratory rate for S-G filtration, EDR and RSA methods for all leads

The boxplots delivered in Fig. 3 present information about errors in determining the RR for each algorithm depending on the ECG lead. The charts were prepared based on the data in Tables 4-7.

a) b) c) d)

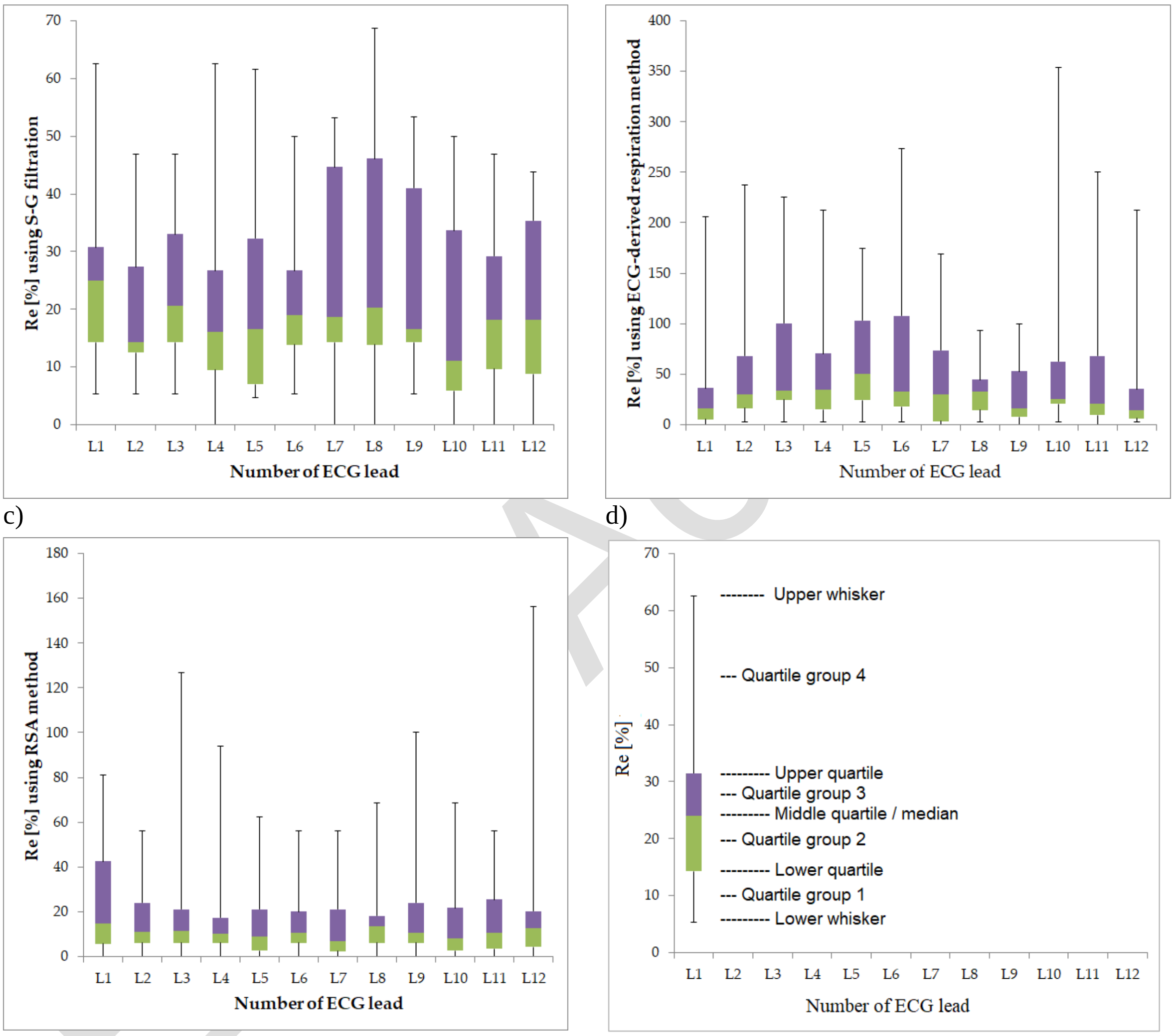

Fig. 3. Box plot of relative errors in determining the respiratory waves by (a) S-G filtration; (b) EDR method; (c) RSA method and (d) introduction to box plot.

The box plots shown in Fig. 3 are used to visually summarize and compare groups of data. A box plot uses the median, approximate quartiles and lowest and highest data points to convey the level, spread and symmetry of the distribution of data values [27, 28]. The parameters shown in Fig. 3d denote: the upper and lower whisker - the maximum and minimum value, the upper and lower quartile - Q1 and Q3, median - Q2, the quartile group - the set of data between quartiles.

The smallest value of the median of the relative error was recorded for the RSA method in lead number L7 and it is equal to 6.70%. For the EDR method, the lowest value of the median of the relative error was recorded for lead L12 and amounts to 14.19%, although the measurement errors are undoubtedly highest for subject no. 12. For subjects 1-10, the best results are obtained from leads L7 and L8. In the case of S-G filtration, the smallest relative error occurs for lead L10 with a median of 11.01%. For -G filtration, the median value of the relative error is 18.75%

5.2. Research of effectiveness of determination of ECG signal derived respiratory rate for the S-G, EDR and RSA methods in relation to the BMI parameter

In the next stage, the dependence of the effectiveness of estimating the RR from the ECG on the BMI and TV parameters was checked. The first parameter is closely related to abdominal fat, whereas TV is related to the lung volume. The median of the relative errors for all respectively subjects of each lead in relation to the BMI parameter is shown in Fig. 4.

a)
b)
c)

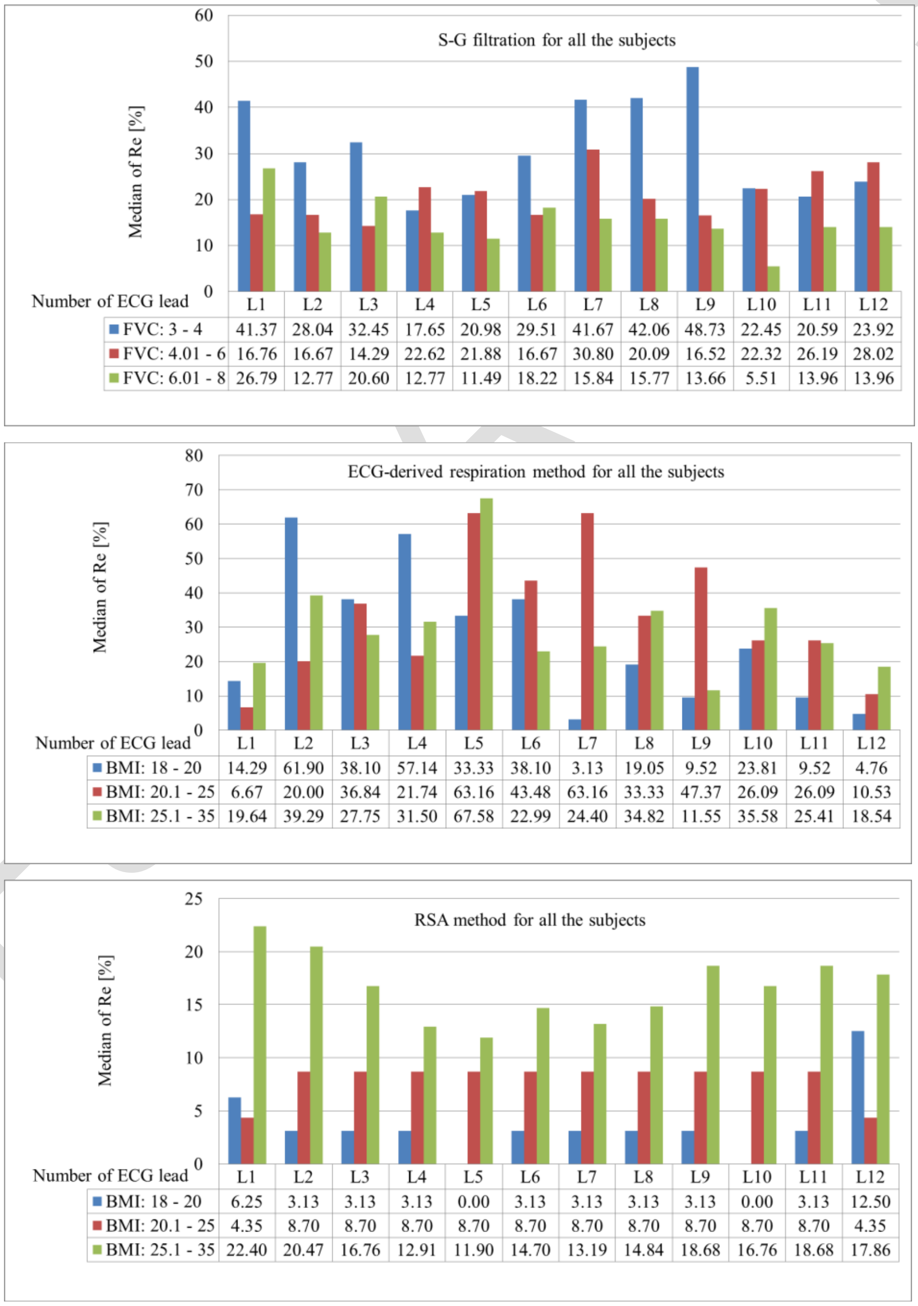

Fig. 4. Graphical presentation of statistical data for BMI with measurement results for medians of relative errors for the following methods: (a) S-G, (b) EDR, (c) RSA.

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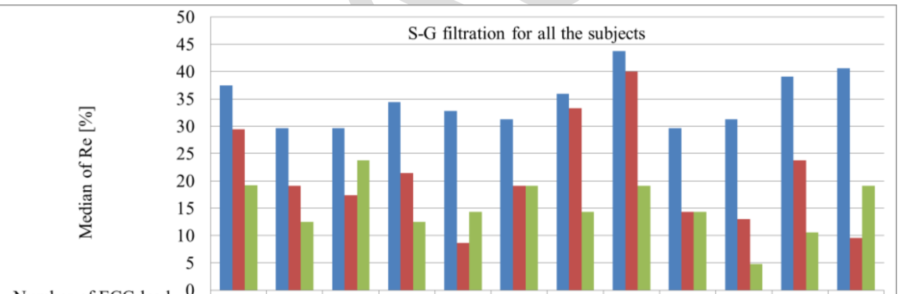
On the basis of the analysis of the influence of the BMI parameter on the effectiveness of determining the RR using the ECG, the graphs presented in Fig. 4 show that lead L10 provides a suitable source for use in the S-G algorithm. Errors for individual BMI ranges: 18-20; BMI: 20.1 – 25; BMI: 25.1 – 35 are equal to: 12.5%; 6.7% and 19.2%, respectively. For this method, the correct value of the BMI parameter gives the highest efficiency of estimating the RR (although for BMI: 25.1 – 35, the smallest relative error was recorded in lead L2). In the case of the EDR method, no clear influence of the BMI value on the relative error was observed. The median value of the lowest relative error for BMI: 18-20 was observed for lead L7 and it is equal to 3.13%. For BMI: 20.1 – 25, the lowest median value was recorded for lead L1 and it is 6.67%. For BMI: 25.1 – 35, the median value of the relative error is the lowest for lead L9 and amounts to 11.55%. For the RSA method, a direct influence of the BMI value on the value of the relative error can be observed. The greater the value BMI also involves the greater degree of error. The smallest median values of relative errors for BMI: 18-20 occurred for leads L5 and L10 and they are equal to 0%. For BMI: 20.1 – 25, the smallest error value was recorded in leads L1 and L12 – 4.35% and for BMI: 25.1 – 35, the smallest value occurred for lead L5 – 11.90%.

5.3. Research of effectiveness of determination of ECG signal derived respiratory rate for the S-G, EDR and RSA methods in relation to TV, FEV1 and FVC parameters

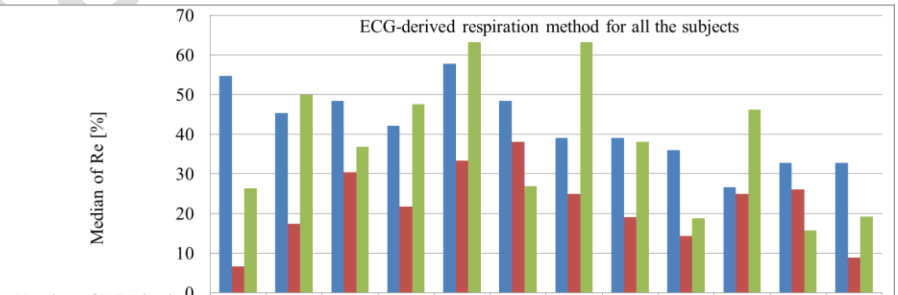
Parameter ranges for BMI, TV, FEV1 and FVC were selected empirically. Fig. 5 presents the dependence of the effectiveness of determining breath from the ECG, taking into account the TV parameter.

a)



Number of ECG lead	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
Tidal Volume: 0.5 - 1	37.50	29.69	29.69	34.38	32.81	31.25	35.94	43.75	29.69	31.25	39.06	40.63
Tidal Volume: 1.01 - 1.3	29.41	19.05	17.39	21.43	8.70	19.05	33.33	40.00	14.29	13.04	23.81	9.52
Tidal Volume: 1.31 - 2	19.23	12.50	23.81	12.50	14.29	19.05	14.29	19.05	14.29	4.76	10.53	19.05

b)



Number of ECG lead	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
Tidal Volume: 0.5 - 1	54.69	45.31	48.44	42.19	57.81	48.44	39.06	39.06	35.94	26.56	32.81	32.81
Tidal Volume: 1.01 - 1.3	6.67	17.39	30.43	21.74	33.33	38.10	25.00	19.05	14.29	25.00	26.09	8.82
Tidal Volume: 1.31 - 2	26.32	50.00	36.84	47.62	63.16	26.92	63.16	38.10	18.75	46.15	15.79	19.23

c)

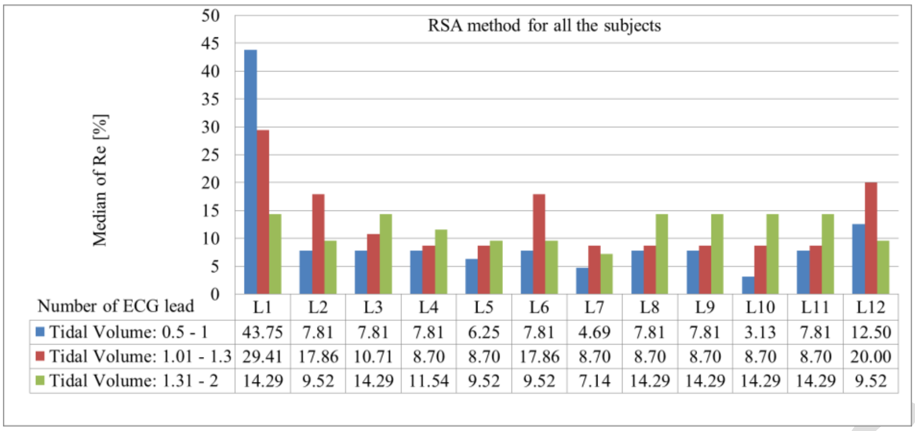


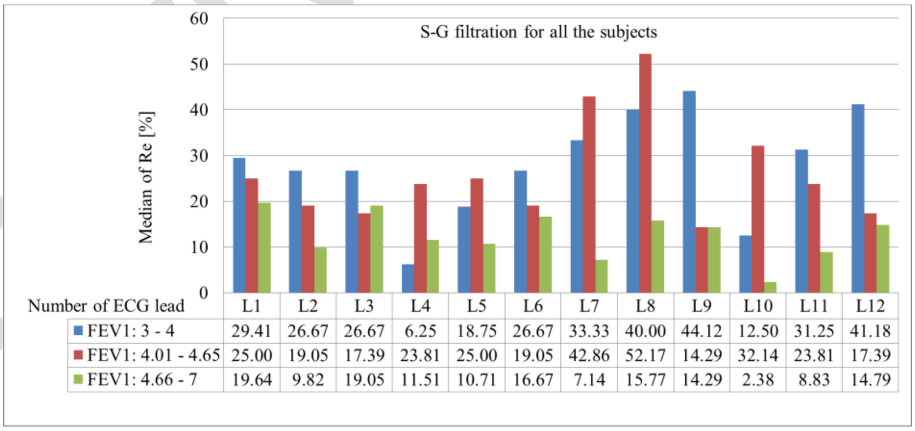
Fig. 5. Graphical presentation of statistical data for Tidal Volume parameter with measurement results for medians of relative errors for the following methods: (a) S-G, (b) EDR, (c) RSA.

For S-G filtration, we can observe that the higher TV value, the smaller values of the relative error. In the case of the TV range: 0.5 – 1, the smallest relative error occurs for L2, L3 and L9 and it is equal to 29.69%.

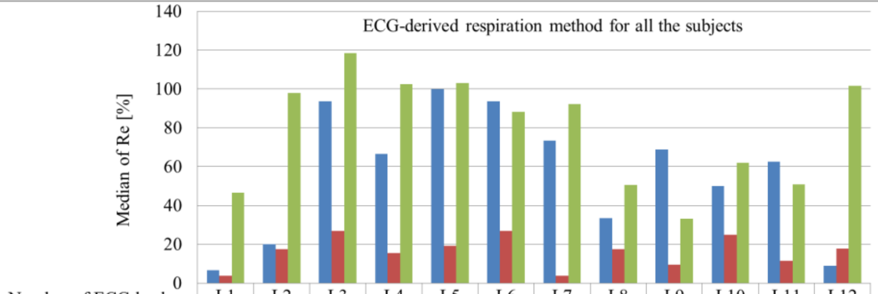
In the range of TV from 1.01 to 1.3, the smallest relative error is obtained for the L5 lead and it is 8.7%. For the range of TV: 1.31 – 2, the smallest relative error occurs on the L10 lead and is 4.76%. In the EDR method, the lowest value of the relative error occurs for the L10 lead for the TV range: 0.5 – 1 and it is 26.56%. For the TV range: 1.01 – 1.3, the lowest value of the relative error is also for the L1 lead and it is equal to 6.27%. In the range of TV parameter: 1.31 – 2, the lowest value of the relative error was recorded for the L11 lead and it is 15.79%. In the case of the RSA method for the range of TV: 0.5 – 1, the lowest value of the relative error is 3.13% and occurs for the L10 lead. In the range of TV: 1.01 – 1.3, the lowest value occurs, among others, for L4, L5, L7 – L11 and it is 8.70%. In the range of TV: 1.31 – 2, the lowest relative error is observed for lead L7 and it is 7.14%.

Fig. 6 shows the relation of effectiveness of determining respiration rate based on the ECG, taking into account the FEV1 parameter.

a)

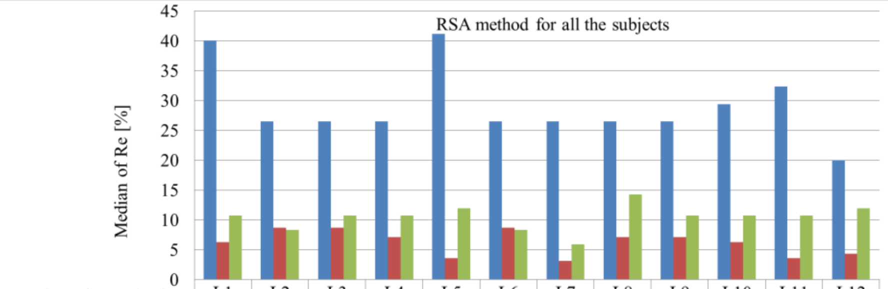


b)



Number of ECG lead	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
FEV1: 3 - 4	6.67	20.00	93.75	66.67	100.00	93.75	73.33	33.33	68.75	50.00	62.50	8.82
FEV1: 4.01 - 4.65	3.85	17.39	26.92	15.38	19.23	26.92	3.85	17.39	9.52	25.00	11.54	17.86
FEV1: 4.66 - 7	46.49	97.93	118.42	102.38	103.01	88.16	92.29	50.63	33.06	61.90	50.75	101.69

c)



Number of ECG lead	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
FEV1: 3 - 4	40.00	26.47	26.47	26.47	41.18	26.47	26.47	26.47	26.47	29.41	32.35	20.00
FEV1: 4.01 - 4.65	6.25	8.70	8.70	7.14	3.57	8.70	3.13	7.14	7.14	6.25	3.57	4.35
FEV1: 4.66 - 7	10.71	8.33	10.71	10.71	11.90	8.33	5.95	14.29	10.71	10.71	10.71	11.90

Fig. 6. Graphical presentation of statistical data for the FEV1 parameter with measurement results for medians of relative errors for the following methods: (a) S-G, (b) EDR, (c) RSA.

In the case of S-G filtration, the smallest error was recorded in the FEV1 parameter for the range from 4.66 to 7 for lead L10 and it was equal to 2.38%. Within this range, the median error for leads L1 – L12 was the smallest and amounted to 12.55%. In the case of the range 4.01 – 4.65, the median error was higher and amounted to 26%, and for the range 3 – 4 it was 28.07%. For the EDR method, the smallest error occurred in leads L1 and L7 and it was in the range of FEV1: 4.04 to 4.65 and is 3.85%. For this range, the average lead error is also the smallest and amounts to 16.24%. For the range 3 – 4 the median error was 56.46% and it occurred for the range 4.66 – 7 it was 78.89%. In the RSA method, the smallest error occurred in the FEV1 range: 4.01 to 4.65 in lead L7 and it was 3.13%. In the case of this range, the median error recorded in leads L1 – L12 was the smallest and was equal to 6.22%. For the range 3 – 4, the median of the error was 29.02%, and in the range 4.66 – 7, it was 10.42%.

Fig. 7 illustrates the dependence of the effectiveness of determining respiration rate on the basis of the ECG, taking into account the FVC parameter.

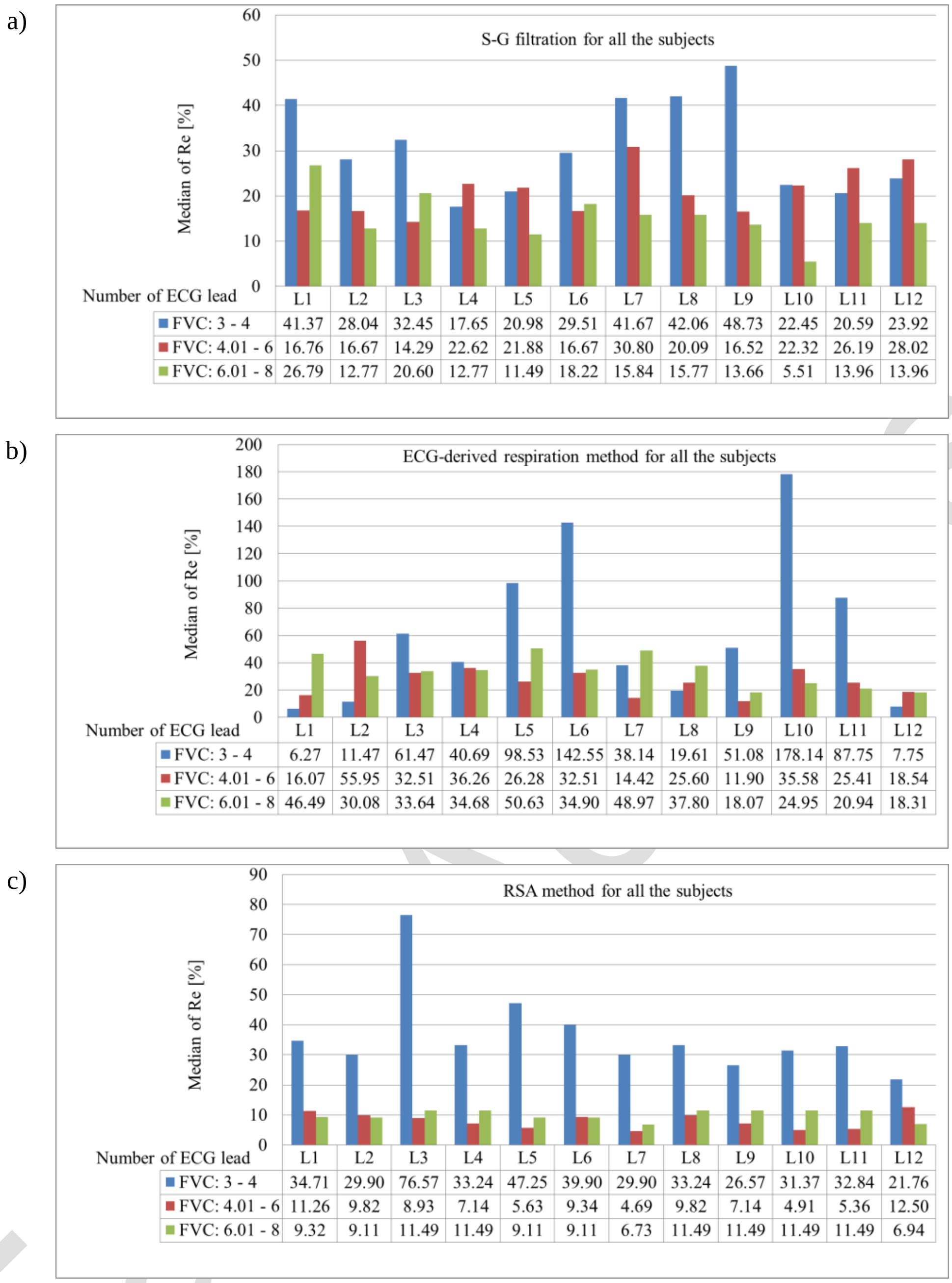


Fig. 7. Graphical presentation of statistical data for FVC parameter with measurement results for medians of relative errors for the following methods: (a) S-G, (b) EDR, (c) RSA.

In the case of S-G filtration, the smallest error was recorded for lead L10 in the FVC range: 6 to 8 and was 5.51%. Also for this range, the median of the error from leads L1 – L12 was the lowest and was equal to 15.11%. In the range of FVC: 3 to 4, the median of the leads was 30.78% and in the range of 4.01 – 6 it is 21.07%. For the EDR method, the smallest error occurred in the FVC range: 3 to 4 and amounted to 6.27%, while the smallest error from all leads L1-L12 occurred in the range of 4.01 – 6 and was equal to 27.59%. For the FVC1: 6 to 8 range, the average error across all leads was 33.29%. In the case of the RSA method, the smallest error occurred in lead L7 in the FVC range: 4.01 to 6 and it was 4.69%. For this range, the average error of all leads L1–L12 is 8.05%. For the FVC range: 3 – 4, the error was 36.44% and for the FVC range: 6 - 8 it was 9.94%.

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5.4. Bland-Altman Plot

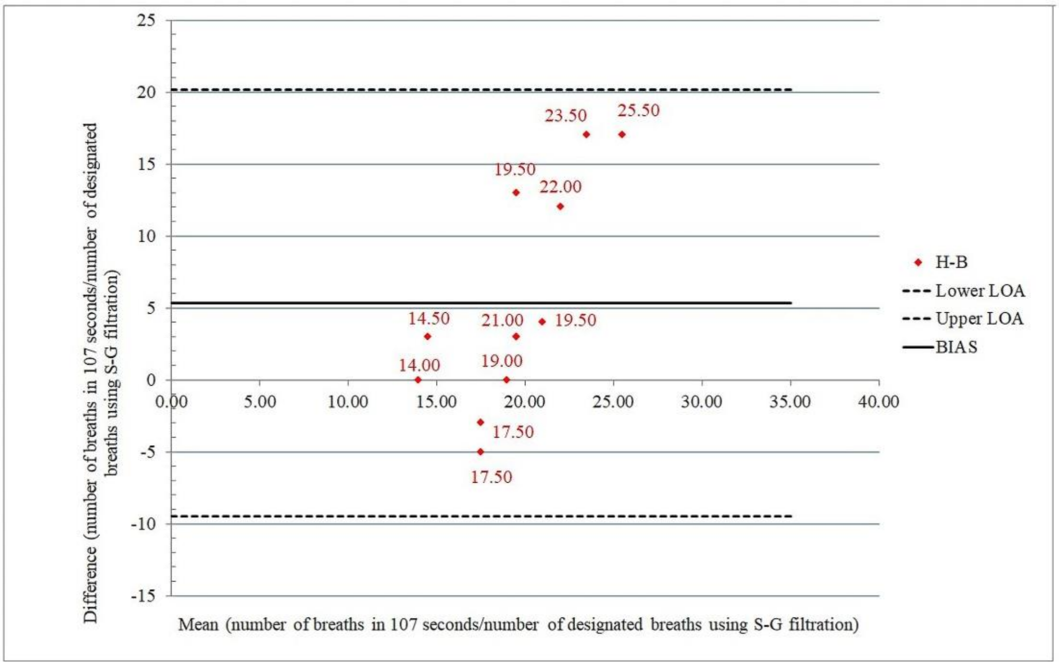
The correlation test between the estimated RR obtained by the reference method and the tested methods: S-G filtration, EDR and RSA, was performed using Bland-Altman (B&S) plots.

The B&A chart was conducted to validate clinical measurement [29–31]. The purpose of this study is to evaluate the compatibility of different methods for determining respiratory rate from the ECG with the traditional method, that is, counting breaths by observing chest movements. It is important to see to what extent these results differ. The differences between the results for each method are expected to be small. The B&A chart introduces the parameters: BIAS and lower and upper "*limits of agreement*" (LOA). BIAS is the mean differences. The 95 percent LOA is calculated as the average of two values, minus and plus 1.96 standard deviations. The result of the calculation is a scatter plot of the variables using the X axis (mean) and Y axis (difference).

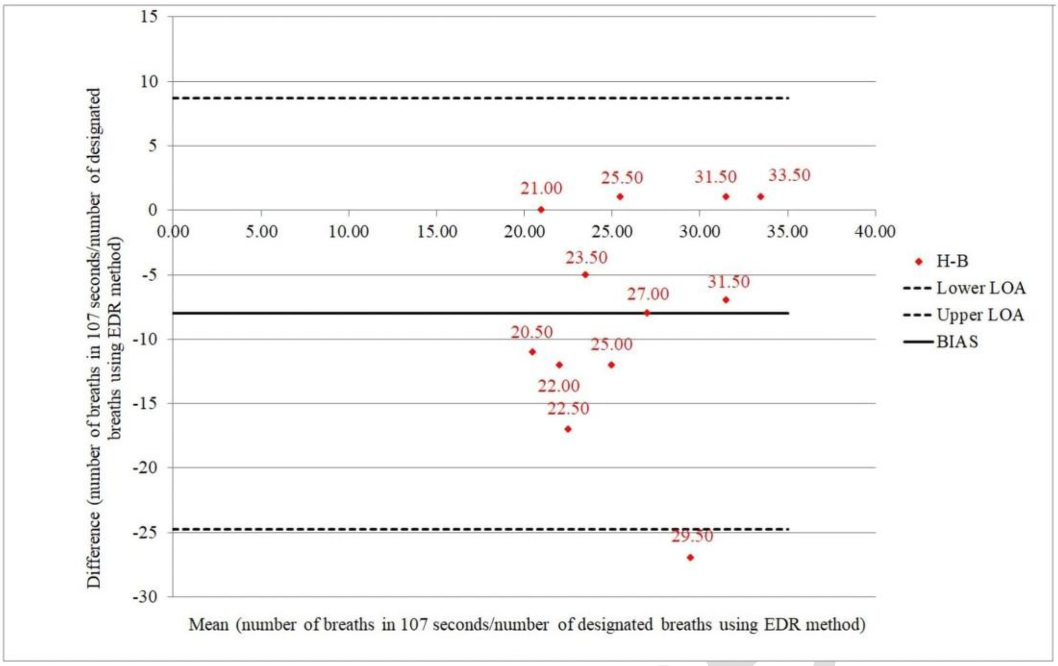
Due to the generally smallest Re values for all 12 subjects (not taking into account physiological parameters), the L7 lead was chosen for B&A analysis. The results of the analyses are shown in Fig. 8 for S-G filtration (Fig. 8a), EDR (Fig. 8b) and RSA (Fig. 8c), respectively.

The B&A chart indicates that the S-G filtration (Fig. 8a) method yields lower results than the reference method by an average of 5.55 breaths/107 seconds. The span of the compliance interval is as high as 29.59 breaths/107 seconds of measurement, which translates into a large measurement error. In the case of the EDR method (Fig. 8b), the BIAS is higher by 8 breaths/107 seconds relative to the classical breath count method (reference method). In this case, the limits of agreement are very large at 33.43 breaths/107 seconds. In Fig. 8c, it can be seen that the BIAS between the value obtained by the RSA method and the classic value is equal to 0, and the limits of agreement is the lowest for all 3 methods at 17.53.

a)



b)



c)

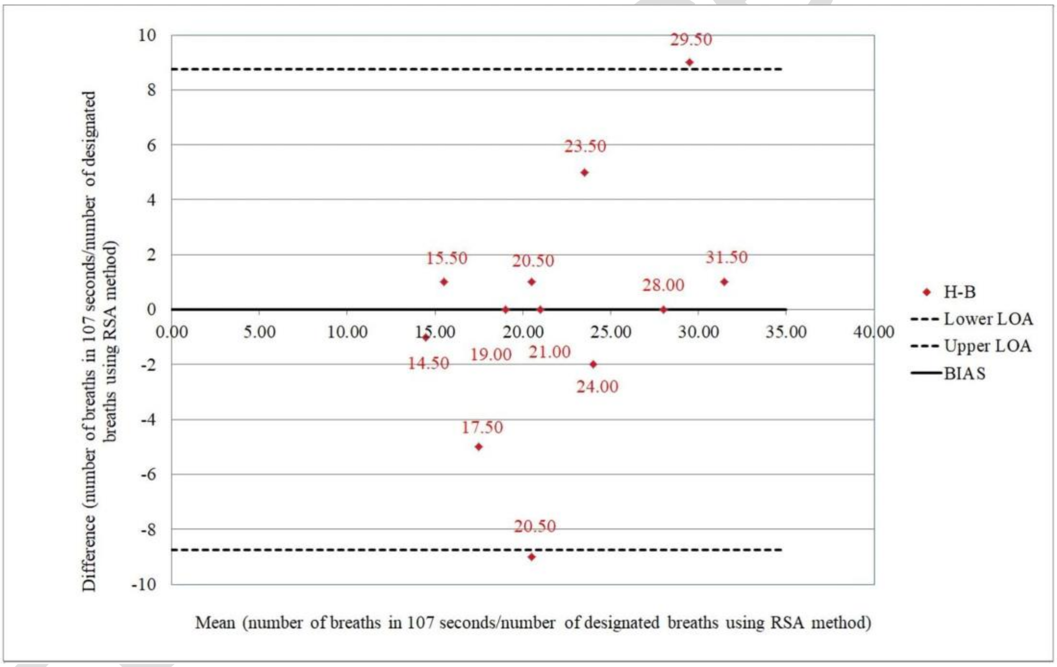


Fig. 8. Bland-Altman Plot of the (a) S-G filtration, (b) EDR method, and (c) RSA method (H-B – differences between reference and investigated methods, LOA - limits of agreement, BIAS - mean difference between reference and investigated methods).

6. Conclusions

The conducted research presents the possibility of using the ECG waveform to create a *respiratory wave* (RW) and estimate the *respiratory rate* (RR) parameter. In particular, it is possible to use the *Savitzky-Golay* filtering (S-G) method to extract the RW from the ECG waveform with a larger number of samples, compared to the other methods. The optimal values of the S-G filter parameters were selected. This method shows significant research potential, allowing the determination of a parameter that corresponds to chest activity during breathing over time. Besides, there are indications that it may not be susceptible to cardiovascular arrhythmias, which differentiates it from the other two methods.

It is also noted that there is a correlation between the RR estimation error and the parameters BMI (*Body Mass Index*), TV (*Tidal Volume*), FEV1 (*Forced Expiratory Volume in 1 second*) and FVC (Forced Vital Capacity). Nevertheless, further studies with a larger number of patients are needed to categorically confirm the above correlations.

In addition, the investigated methods (ECG-Derived Respiration - EDR, Respiratory Sinus Arrhythmia - RSA and S-G) feature different RR estimation errors depending on the choice of ECG leads. It is possible to select the optimal lead depending on the method. By using a study group of 12 subjects with different criteria (BMI, TV, FEV1 and FVC), it can be stated that further studies are warranted. This study should lead to the determination of the optimal ECG lead, in the context of the listed parameters.

An embedded system using an air cuff surrounding the chest with an integrated piezoresistive sensor was applied as a reference device to enable the registration of the respiratory wave and determining the RR. In the next version of the device, a sensor executed in the MEMS technology will be used.

The information regarding the RR and the recording of the RW during sleep or sport will allow medical personnel to perform a diagnosis sooner. Using digital signal processing methods and implementing an artificial neural network, it will offer the means to establish the abnormalities in the ECG signal faster and generate a representative respiratory signal combined with determining its pattern.

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