Respiratory Information Extraction from Electrocardiogram Signals

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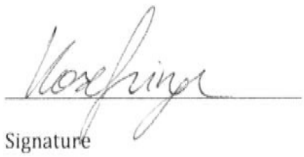
JÜRGEN KÖSEL		13/12/2010

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ABSTRACT

Respiratory Information Extraction from Electrocardiogram Signals

Gamal El Din Fathy Amin

The Electrocardiogram (ECG) is a tool measuring the electrical activity of the heart, and it is extensively used for diagnosis and monitoring of heart diseases. The ECG signal reflects not only the heart activity but also many other physiological processes. The respiratory activity is a prominent process that affects the ECG signal due to the close proximity of the heart and the lungs. In this thesis, several methods for the extraction of respiratory process information from the ECG signal are presented. These methods allow an estimation of the lung volume and the lung pressure from the ECG signal. The potential benefit of this is to eliminate the corresponding sensors used to measure the respiration activity. A reduction of the number of sensors connected to patients will increase patients' comfort and reduce the costs associated with healthcare. As a further result, the efficiency of diagnosing respirational disorders will increase since the respiration activity can be monitored with a common, widely available method. The developed methods can also improve the detection of respirational disorders that occur while patients are sleeping. Such disorders are commonly diagnosed in sleeping laboratories where the patients are connected to a number of different sensors. Any reduction of these sensors will result

in a more natural sleeping environment for the patients and hence a higher sensitivity of the diagnosis.

Contents

Appendix 1: (Notation and Abbreviation):

Upper case letters ex. X: used for matrix representation.

Lower case letter ex. x: used for column vectors.

□□: is the ith column vector of matrix X.

□□□: is the ith row jth column element of matrix X.

□□: column vector of a signal in time sampled uniformly.

(SA): Sinoatrial node

(AV): atrioventricular node.

ECG: Electrocardiogram.

ANS: Autonomous nervous system.

PSD: Power spectral Density.

BPF: Band pass filter.

LPF: low pass filter.

HPF: high pass filter.

ECG1=channel1 ECG: ECG signal recorded from left to right arm.

ECG2=channel2 ECG: ECG signal recorded from left arm to left leg.

VECG: vector ECG a relational plot of ECG1 on x axis relative to ECG2 on y axis.

□□= time instance of the R-peak.

□□= lung volume at R-peak time instance.

□□= lung pressure at R-peak time instance.

□□= feature extracted from ECG and correlated with □□ or □□.

BSS: Blind Source Separation.

PCA: Principal Component Analysis.

PC: Principal Component.

R-Peakn= distance between R point to base line of channel n ECG.

Q-RPeakn= difference between Q point to R point of channel n ECG.

R-SPeakn= difference between R point to S point of channel n ECG.

PulseArean= area of the one pulse of ECG of channel n.

Q-SArean= area of ECG pulse of channel n between the time instance of Q point to S point time.

Q-RArean= area of ECG pulse of channel n from beginning until R instance (before chapter 9).

(updated on chapter 9 onward) area of ECG pulse of channel n between the time instance of Q point to R point time.

R-SArean= area of ECG pulse of channel n from R instance to the end of the pulse (before chapter 9). (Updated on chapter 9 onward) area of ECG pulse of channel n between the time instance of R point to S point time

RatioArean= The ratio of Q-RArean to R-SArean.

PCAn= construction of the signal using the dominant n principal components.

Corr= correlation coefficient.

1 Introduction:

The electro cardiogram (ECG) signal is one of the most important and most utilized biosignals. It provides many details on the physiological processes that occur in the human body, especially with respect to the function of the heart.

One of the main goals in biomedical systems engineering is to increase the data collected by biosensors in order to provide physician with more information about the physiological state of patients. At the same time, there are increased attempts to reduce the number of sensors connected to the patients in order to increase the patients' comfort. This thesis is a study of the two main respiration parameters, lung volume and lung pressure, and their correlation with the ECG signal. Features from two channels ECG are extracted and correlated independently and collectively with lung volume and lung pressure.

2 Electrical Heart Activity:

The heart is a muscle that is responsible for pumping oxygenated blood through the body. It consists of 4 chambers 2 upper called atria and two lower named ventricles. The blood is pumped through valves from the right

side of the heart to the lung, where oxygen is transferred to the blood, and back to the left side of the heart, which pumps the oxygenated blood to the rest of the body. [12]

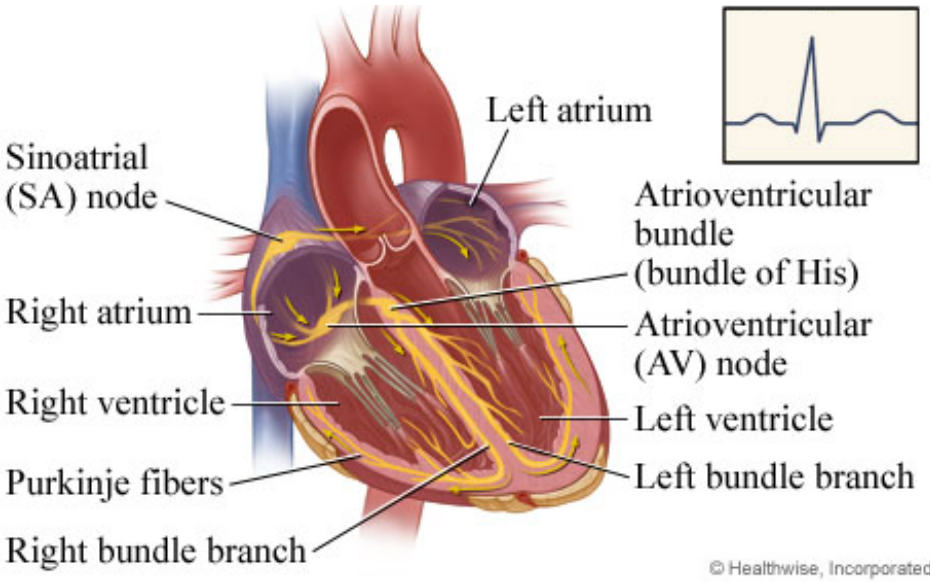

Figure 1: Heart Anatomy [12]

In order to facilitate an effective pumping mechanism the heart is composed of 3 main types of cells:

1- Rhythm generators to control the heart rhythm.

2- Conductors to spread the pacemaker signal.

3- Contractile cells (myocardium) to mechanically pump blood [3].

The rhythm generators produce an electrical signal that is applied through the sinoatrial node (SA) ~~node~~ at the right heart atrium when it is filled with blood. The signal propagates through conductor cells to the right and left atria causing them to contract. This action pushes the blood through valves to the lower ventricles. The signal continues its propagation to the atrioventricular

(AV) node where it is delayed for some time to enable the ventricles to fully fill with blood. The (AV) node then spreads the signal to many bundles divided to the right and left bundles that carry the signal to the contractile cells at the walls of the right and left ventricles causing them to contract. The left ventricles contract before the right to pump blood through the following circuits:

1- Pulmonary Circuit: through lungs to oxygenate the blood and remove the carbon dioxide by right ventricle. [3]

2- Systemic circuit: to deliver oxygen and nutrients to tissues and remove carbon dioxide by left ventricle. [3]

3 Electrocardiogram (ECG):

William Einthoven was the first to reliably measure the electrical activity of the heart in the Netherlands [6]. His efforts led him to win the noble prize in medicine in 1924 [6]. The signal he measured using a sensitive galvanometer was named Electrocardiogram (ECG). This discovery was a revolution in medicine as it enabled physicians to diagnose and indicate heart problems without surgeries by simply noticing the irregularities of the ECG waveform which can detect irregular heart rhythm or myocardial infarction [1].

The electrical activity of the heart is nowadays measured using very sensitive electrodes that are placed on the surface of the skin. The number of channels

used to measure ECG varies from 1, 2, 3, 6, 12 or more depending on the application and on how much information needs to be extracted from the heart activity [1].

3.1 Measuring Electrodes:

The electrical activity in living tissues is induced by currents of electrical charge carriers that typically consist of ions [1]. In electronic circuits the charge carriers are formed by electrons or holes. To interface between these two different systems electrodes are required.

Electrodes implement the transformation from ionic conduction to electric conduction through chemical reactions. They are composed of metal, saturated salt from that metal and an electrolyte made of common ions. For instance, an electrode commonly used is made of silver metal, silver chloride salt and sodium chloride electrolyte [1]. These bio potential electrodes are very sensitive to biosignals. However, they depend on electrochemical reactions that create a double layer of charges that is vulnerable to any movement [1]. Therefore, they need to be attached to the skin properly.

Electrodes can be modeled as an RC system as shown in figure 2. E1 is the electrode potential and Ce is the capacitance resulting from the generation of the double layer discussed above. Re is the resistance of the conduction.

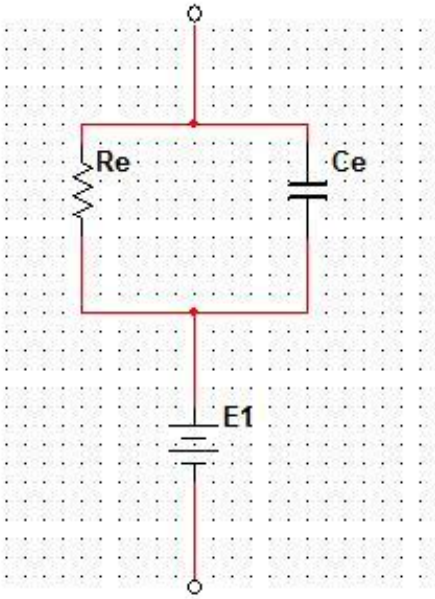

Figure 2: Simple Electrode Model

There are more complex models than discussed above that include, for example, different layers of the skin surface as shown in figure 3. The Dermis is the inner skin layer, Epidermis is the upper layer and the paste fixes the electrode on the skin.

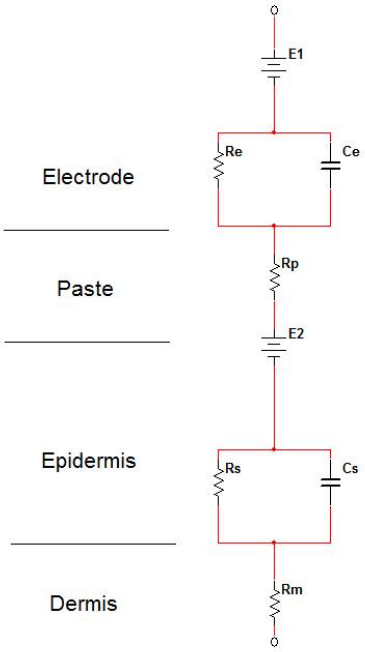

Figure 3: Complex Electrode Model

Other types of electrodes include:

- Glass micropipette electrodes.
- Needle electrodes.
- Micro array electrodes.
- Dry electrodes. [1]

3.2 ECG wave forms:

Einthoven analyzed the ECG waveform by dividing ECG wave into 5 main waves named P, Q, R, S and T.

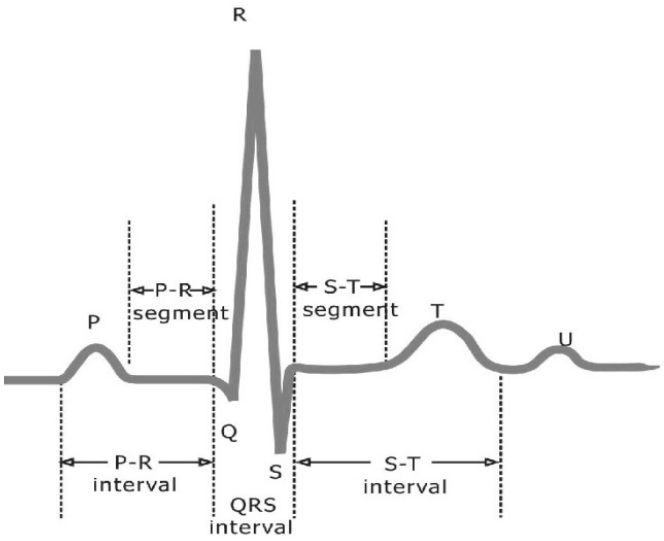

Figure 4: ECG waveform model

Each of these waveforms is a reflection of the heart's operation, which can be described as follows:

- P wave: is the reflection of atrial depolarization after the SA node was activated. The amplitude is lower than 300 μV and the duration is 0.120 s. The spectrum includes frequencies that vary from 10 to 15 Hz [1].
- Q wave: represents the split of the electrical heart signal coming from the AV node into the two fiber bundles to the left and right ventricles [12].
- R wave: this is the main instance in the ECG signal as it marks the contraction of the left ventricles [12]. This wave has the highest amplitude of around 3 mV. Thus it is often used for heart beat detection Algorithms [1].
- S wave: following the left ventricle the right ventricle contracts generating the S wave [12].

All the three Q, R and S together are named QRS complex with duration from Q to S varies from 0.070s to 0.110s.

- T wave: is a low frequency wave that corresponds to the relaxation of the ventricles [12] [1].

In addition to the waves there are also main time segments that can be summarized as follows:

- ST segment: is the time when both ventricles are contracting [1].
- RR interval: is the entire pulse interval from the R peak of one pulse to the next. This time segment may be analyzed to indicate any arrhythmias.
- PQ segment: is the delay time that is imposed by the AV node in order to delay the signal until the blood fills the ventricles [12].
- QT segment: the time of one beat from the contraction of the first ventricle until both ventricles relax. This time segment is also used for diagnostic purposes [1].

4 Respiration:

Oxygen is very important for the biological operations of human cells. It is the source of energy and used in the metabolism process, and a continuous supply is essential. As a result of metabolism and other physiological process, some harmful elements are generated such as carbon dioxide. The respiratory system in addition to the cardiovascular system is responsible for oxygen delivery to cells and the removal of carbon dioxide. The respiratory system works as the supplier to blood and the cardiovascular system

transports the oxygenated blood to cells, extracts the carbon dioxide saturated blood and deliver it back to the respiratory system for it to extract carbon dioxide and oxygenate the blood again.

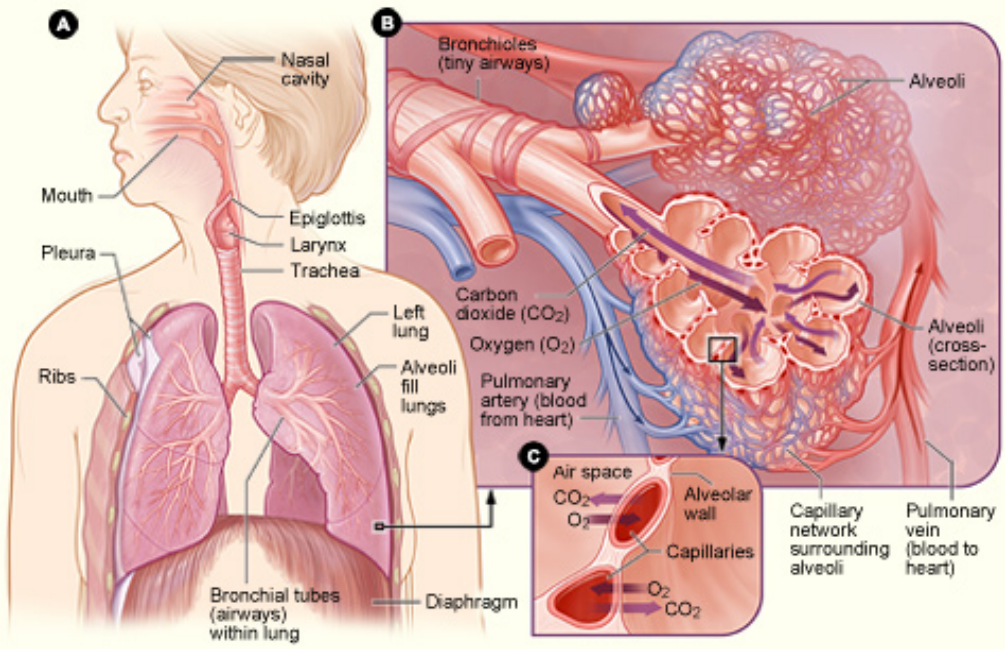

Figure 5: Respiratory system [12]

The Respiratory system consists of three main groups, which are airways, lungs and blood vessels. The airways are tubes that carry the air through the nose, larynx, trachea and bronchi tubes. The main processes of respiration are inhalation and exhalation. Inhalation process occurs when muscles called diaphragm contract, triggered by a signal from the brain transported through spine, increasing the lungs size and forcing air inside the lungs. During this process, the oxygen rich air fills the lungs. Then, exchange of oxygen and carbon dioxide gases process starts replacing the oxygen in lungs with carbon dioxide for exhaling and the blood is enriched with oxygen and sent by cardio system to body. The diaphragm then relaxes decreasing lung size and pushing carbon dioxide out. [12]

The above process is vital to the body to be sound. However, diseases might interrupt this operation and cause implications if not treated. Some of these diseases, for example apnea, affect patients while sleeping, which makes it very hard for patients to be aware of and get the treatment. Sleep apnea is a respiratory disorder that occurs when a cessation of breathing happens that last from a few seconds to minutes and can repeat over 30 times per hour [12].

Apnea occurs when the airways collapse and hence the air faces a blockage and cannot enter the lungs. This type is named obstructive apnea and it is the most common type, and, usually, it is accompanied with snoring. Obstructive apnea usually affects overweight and old persons. The less common type is named central apnea that happens when the signal coming from the brain to the diaphragm is not sent due to a disorder in the nervous system. It usually affects people that have certain medical conditions or patients using certain medicines [12]. Sleep apnea is chronic and, since it decreases the oxygen level of the blood, has many health implications. Some of which are:

- Reduction in blood oxygen saturation & arousal events.
- Sleeping during day, irritability tiredness, impaired concentration and reduction of learning capabilities, social problems in the work place and traffic accidents.
- Generating diurnal hypertension and sever cardiovascular health implications that can lead to death. [11]

Thus, early diagnose of respiratory diseases is needed. However, many people are not aware of these disorders since it occurs when they are

sleeping. To diagnose respiratory disorders, patients should perform a sleep study. The test used is called polysomnogram and it requires sleeping labs, which are available only in highly specialized clinics. In this test, the patient sleeps at the lab while attached to a number of different sensors that measures the following:

- Brain activity
- Eye movement and other muscle activity
- Breathing, heart rate, and blood pressure
- Airflow.
- Oxygen level in blood. [12]

The sensors are fixed on the scalp, fist, finger and face causing a lot of inconvenience to the patients and disturbing their sleep. In turn, this might cause a false diagnosis; hence, more effective and efficient ways of diagnosing respiratory diseases are sought after.

5 ECG and Respiration:

To increase patients' comfort and be able to diagnose respiration disorders a lot of research was done recently to increase the information fetched from one sensor and hence reduce the sensors connected to patients. Most of these researches were concerned on the classification of certain disorders like apnea. Some of them focused on time, frequency analysis or autoregressive models to classify respiration disorders [11]. ECG signal recorded from skin

electrodes can give insight not only to heart activity but also to other physiological processes. Since the ECG signal propagates through the human body it is affected by various physiological processes. This provides the opportunity to extract information about these processes from the ECG signal. For instance, it was found that the signal carried in the ECG that ranges from 0 to 0.5 Hz is linked to the autonomic nervous system (ANS) function. Signal from 0.15-0.5 Hz is a reflection of vagal tone that affects the heart when only the parasympathetic nerve fibers are controlling the heart labeled high frequency. The frequency range from 0.02-0.15Hz is the reflection of the increase of orthosympathetic component activity. The range from 0.0033-0.02 Hz reflects the thermoregulation activity that keeps the body temperature within limits. Moreover, it was noticed that during non-rapid eye movement - first 3 stages of sleeping - the power spectral density (PSD) of the signal is larger for frequencies above 0.3 Hz. On the other hand, the low frequencies have larger PSD in the rapid eye movement or deep sleep. [11]

Respiration is one of most prominent process that can be extracted from the ECG signal. When the chest moves during respiration, the ECG signal is modulated due to the change of the heart's position relative to the electrodes and the change of the impedance of the medium (body tissues) that ECG signal propagates through [4]. Hence, the ECG signal may be used to derive information about respiration activity. Attempts to diagnose diseases and derive information of the respiration system employed algorithms which extract ECG features such as the R-Peak, QRS complex, etc. and measure the correlation of such features with respiration using different numbers of leads. Though the single lead ECG is the simplest and most comfortable to

patients, distinguishing the vital variability of respiration from noise is difficult as common noise information, which is available when using multi-lead ECG, is not present [13].

This study is examining the main respiration components represented by lung volume and lung pressure variations during breathing. Correlation between respiration elements changes and features extracted from the ECG signal are measured. These features are handled independently from different channels and collectively using 2 channels vector ECG (VECG). Also, the principle component analysis (PCA) is used to improve the correlation with lung volume and lung pressure.

6 Methods:

6.1 Signal Recording:

Signals from 8 persons (7 males and 1 female) of different ages that vary from 18 to 35 with mean 28 and standard deviation of 5 years were used in this study. The disease history for the subjects was unknown. The system used for the measurement is the Biopac system that can record up to four two-port channels at the same time. The channels were used to measure the following:

- Channel1 (ECG1): This channel was connected to the electrodes on the left with (+) electrode and right arm with (-) electrode in order to measure the ECG signal. The electrodes were placed just above the hand to ensure

minimal interference with neural activities. It was found by experiments that signals picked up from this position suffered from less noise than those picked up by placing the electrodes higher up on the arm next to the shoulders. The electrode for electrical ground reference was placed on the right leg.

- Channel2 (ECG2): This channel is connected from left arm with (+) electrode to left leg with the (-) electrode.

Both ECG channels were set on the Biopac setting to measure the ECG signal with band pass filter (BPF) with a pass band from 0.05 to 150 Hz. This band is low enough to include the breathing frequency that is around 0.2 Hz for adults.

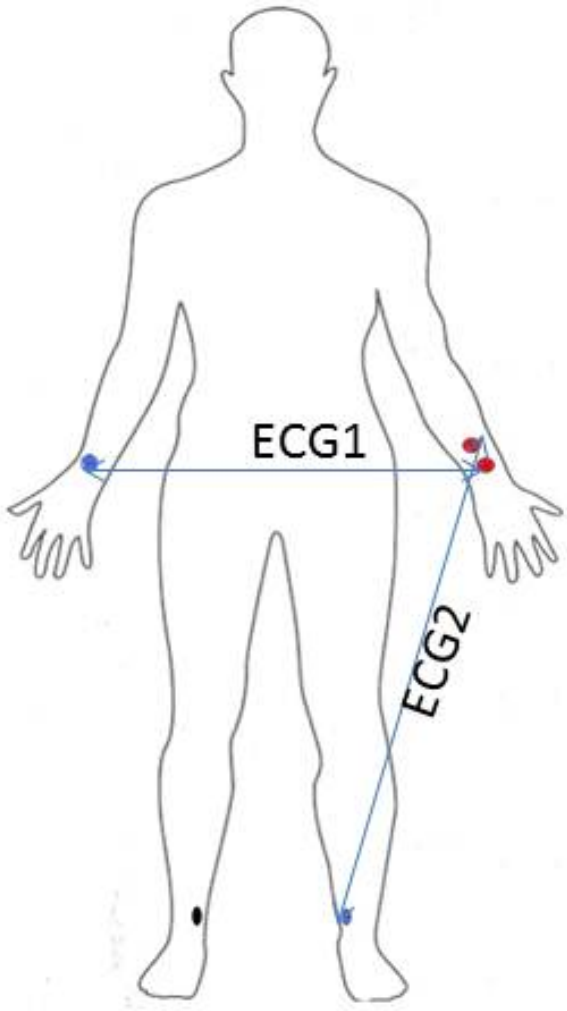

Figure 6: Electrodes positions

- Channel 3: This channel was used to measure the airflow into the lungs during respiration. A medium flow transducer model (300 L/MIN TSD117) was utilized that included a removable mouth piece for easy cleaning and sterilization or replacement (RX117).

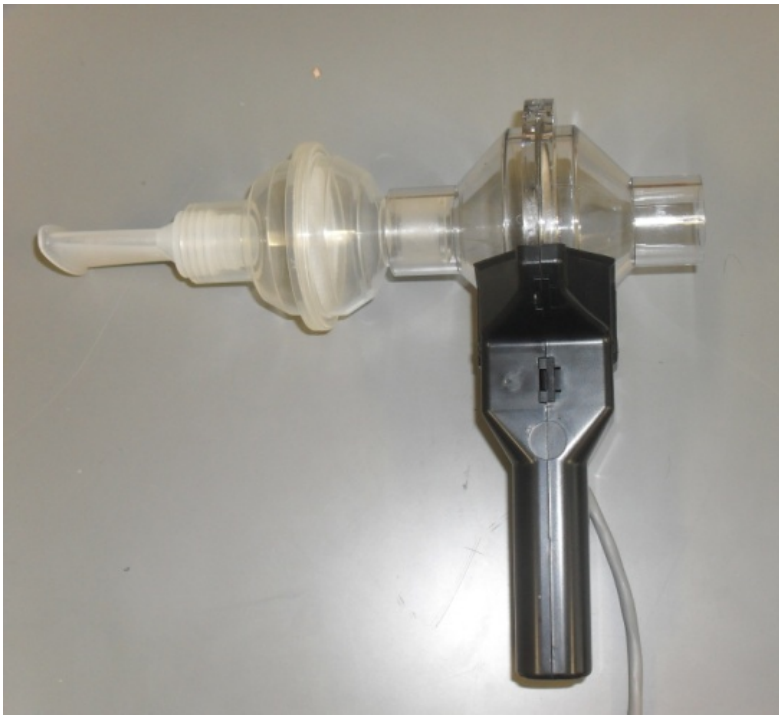

Figure 7: TSD117 Airflow transducer

- Channel 4: This channel is used to measure pressure using a pressure sensor Honeywell 24PC series. The sensor is fixed on a cap with a rubber material to seal the opening and not to allow air leakage. The sensor was mounted to a connector compatible with the Biopac system in order to measure the pressure using the Biopac system.

Figure 8: Pressure sensor Attached to Air Blocking Cap

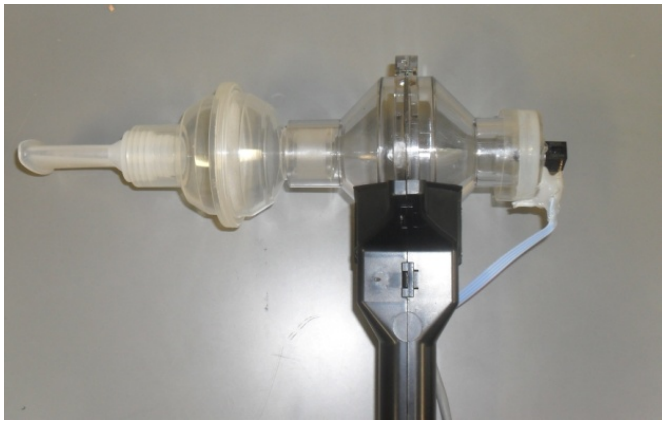

Figure 9: Pressure Sensor Attached to Airflow transducer

The sampling frequency for all channels was 1000 Hz.

Initially, the signal was recorded from the subjects while sitting in chair. However, the signal turned out to be noisy and very sensitive to movements of the subjects. After some experiments, the semi fowler position (sleeping on bed with the back raised to 45 degrees) has proven to give the best performance in terms of least noise and interference.

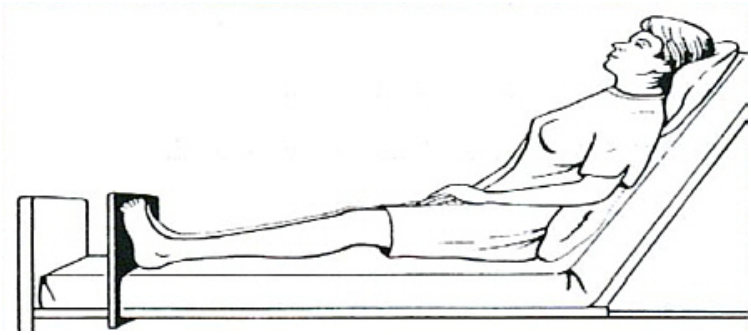

Figure 10: Semi Fowler Position [7]

The subjects were lying on the bed in the semi flower position while relaxing their hands on the sides. In this position, the chins of the subjects were aligned parallel to the ground, which was necessary for the airflow sensor to produce accurate results.

Recordings:

The following experiments were performed to extract signals from the pool of 8 subjects:

- On 8 subjects: 30 seconds of normal respiration while measuring airflow, ECG1 and ECG2 to examine the effect of lung volume change on ECG signal.
- On 6 subjects: 5 different recordings of ECG1, ECG2 and lung pressure at 5 different lung volumes that ranged from the minimum volume at full exhalation to maximum volume at full inhalation. The subjects were asked to fully exhale and then take in some air and apply a linear positive pressure against a closure. The subjects were able to apply a nearly linearly increasing positive pressure for time periods that spanned from 3 ECG pulses to 12 ECG pulses. The subjects were asked to repeat the experiment and take in more air until the fifth time when the maximum lung volume was reached. The subjects were given 1 minute rest between the consecutive measurements in order to make sure that their physiological condition is back to normal. The pressure experiment is done to examine the effect of building lung pressure on ECG as for example in apnea when there is an obstruction in the airways.
- On 6 subjects: the same as in the previous experiment, but the subjects were asked to apply a negative pressure at 5 different lung volumes. The subjects were asked to fully inhale, then release some of the air and then apply a negative linear pressure. In the next step, they released more air before applying negative pressure until the fifth time when the minimum lung volume was reached. The subjects were resting for 1 minute between two tests.

- On 2 subjects: 20 recording of ECG1, ECG2 and lung pressure were measured. At a specific value of the lung volume close to the maximum volume the subjects were asked to increase the positive pressure linearly. The subjects were asked to repeat the experiments 20 times. The test was done with a rest between measurements of 1 minute until the 10^{th} measurement after which they were given a longer rest for 30 minutes before recording the remaining 10 measurements with 1 minute rest between each of them.
- On 2 subjects: ECG1 and ECG2 together with an airflow measurement was for a period of around 5 minutes. The subjects were asked to breathe normally for a minute and then stop breathing for as long as they could to simulate an apnea event. Then, they were asked to breathe again for 1 minute before simulating another apnea event. The subjects repeated this pattern for around 5 minutes. This test was repeated 3 times and the subjects were given a rest for 10 minutes between every experiment. Depending on the subject ability to hold breathe, the cessation of breathe instances lasted from around 40 s to 120 s.

The measurements of the lung volume was easy to conduct, however, the subjects were a little bit uncomfortable with the airflow transducer especially in the last experiment as they were asked to breathe through it for 5 minutes. The most difficulty faced was with lung pressure experiments. Subjects were hardly able to apply linearly increasing positive pressure. Moreover, during the negative pressure experiments most of the subjects failed to produce a linear negative slope and failed to apply pressure for more than 3 sec. Therefore, the negative pressure measurements were ignored in the analysis.

6.2 Signal Processing Techniques:

Different signal processing techniques were used in order to extract potential features from the ECG signal and try to correlate them with lung volume and lung pressure. The lung volume was obtained by integrating the airflow signal after removing its mean. Also, both ECG signal and volume signal were filtered with a BPF with pass band from 0.2 to 40HZ to eliminate high frequency noise and any DC shifts while maintaining the respiration information that has a frequency of around 0.2 Hz and an ECG signal shaped wave form.

6.2.1 One lead ECG:

ECG1 and ECG2 signals recorded were treated separately and some features were extracted from them and correlated with both lung pressure and lung volume. First, R-peak instances □□ (refer to section 3.2) were determined as it is the most significant characteristics of the ECG signal and the corresponding value of lung pressure and lung volume were recorded at that time instance.

1)

2)

Relative to R-Peak time instant □□ all the features of the ECG were extract.

$$\text{[illegible]} = \text{[illegible]} - \text{[illegible]}\ \text{[illegible]} - \text{[illegible]} - 1\text{[illegible]} \ldots\ldots \text{[illegible]} + \text{[illegible]},\ \text{[illegible]}\ \text{[illegible]} = 0,1,2,3\ldots$$

3)

R-Peak: Since the ECG signal travels through the body the R-Peak may be affected by the physical changes during respiration. The R-Peak was the value of the R-peak with respect to the base line.

R-Speak: The R-SPeak was the value found by calculating the difference of magnitudes of the amplitude values of the R-peak and the following S-peak. This value was obtained by defining a window of 40 ms after the R-Peak and searching for the minimum value within this window representing the S-peak and R-SPeak was calculated by taking the difference of the R-Peak and the S-Peak values. The algorithm also works with pulses of negative polarity by identifying the flipped ECG signal by means of R-peak means and variances and flipping the ECG to positive polarity. The R-SPeak is immune to near dc noise that causes a shift of the R-Peak from the base line. However, the variation of the S point itself due to other physiological processes may affect the results. Therefore, calculating both R-Peak from base and R-SPeak provides a more reliable analysis.

The ECG pulses are identified from the ECG signal *S* by setting windows of 0.601 sec centered on the R-Peak instances.

4)

Pulse area: The Pulse area is calculated by integrating the absolute value of each pulse.

Q-Sarea: This area was obtained by getting the minimums around the R-Peaks on a window of 40 ms to identify the Q and S points and then integrate the absolute area in between. This technique is better when Q and S peaks are significant and not very attenuated by noise yet it is difficult to apply when Q and S points are not sharp peaks. Therefore, both areas are complementary to each other and we picked the one that showed better correlation with lung volume and pressure.

To examine the differences between the leading wave from Q to R point and the later wave from R to S point, a new definition of the area from Q to R (**Q-RArea**) is calculated and from R to S (**R-SArea**). In addition, the ratio of Q-RArea to R-SArea abbreviated (**RatioArea**) is also calculated.

6.2.2 Vector ECG (VECG):

The VECG is a graph that is obtained by plotting the ECG1 and ECG2 signals vs. each other (see Figure 11). A relational graph is obtained that determines the relative changes between each channel of the ECG. Although, timing information is absent in the VECG, it offers a tool that indicates the differences of the impacts of lung volume and lung pressure on the different channels and visualizes them. The ECG signal recorded from arm to arm and arm to leg have some differences due to differences between the two channels such as the difference in tissues and the distance the signals travel etc.

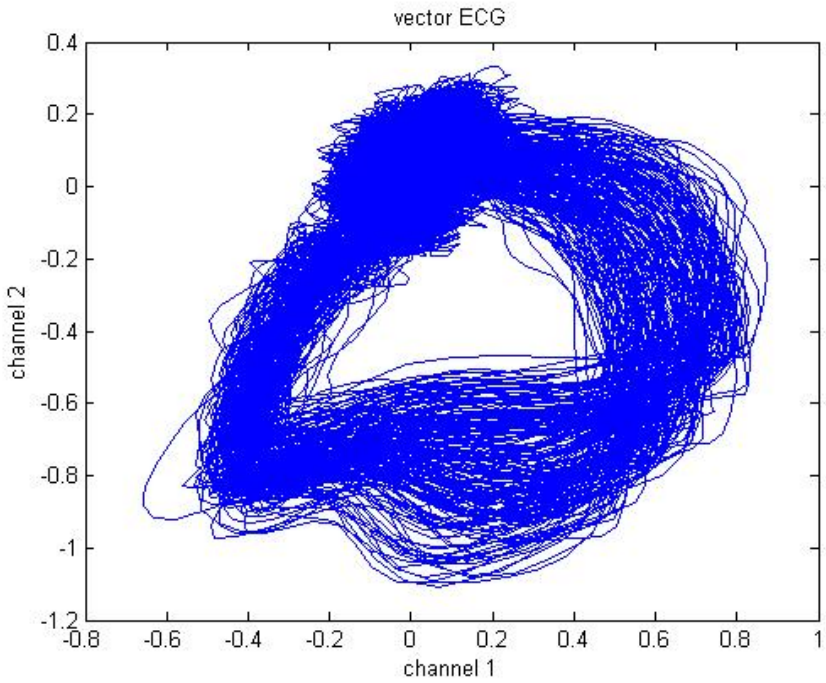

Figure 11: Vector ECG

Some features of the VECG are extracted and correlated with the lung volume and lung pressure. The first feature is the maximum elongation of the VECG. Due to the difference between the different ECG channels, the VECG is shaped nearly as an ellipse. The maximum elongation line is the maximum distance from the zero point to the point touching the VECG curve per pulse. To determine this distance, first the VECG was aligned to lie in the fourth quadrant and the elongation is calculated from the zero point to the max distance (see Figure12).

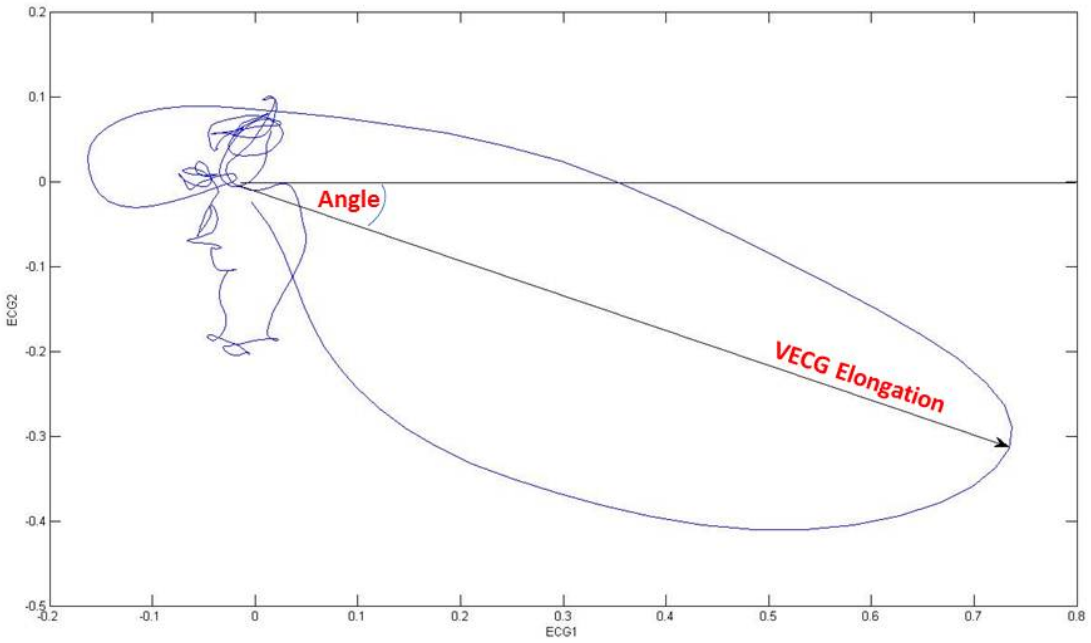

Figure 12: Maximum elongation line and angle

The second feature extracted was the angle of the VECG. This angle is defined as the angle between the maximum elongation line and the positive x-axis.

The last feature extracted is the area enclosed by one cycle from the VECG. This area is calculated by the embedded matlab function polyarea.

All the previous features were measured and correlated with the lung volume and lung pressure values at the R-Peak. For example, as shown in figure 13, at the R-peak instance of each ECG cycle, the value of the lung volume was evaluated and correlated with the value of the maximum elongation line of the VECG of the same ECG cycle.

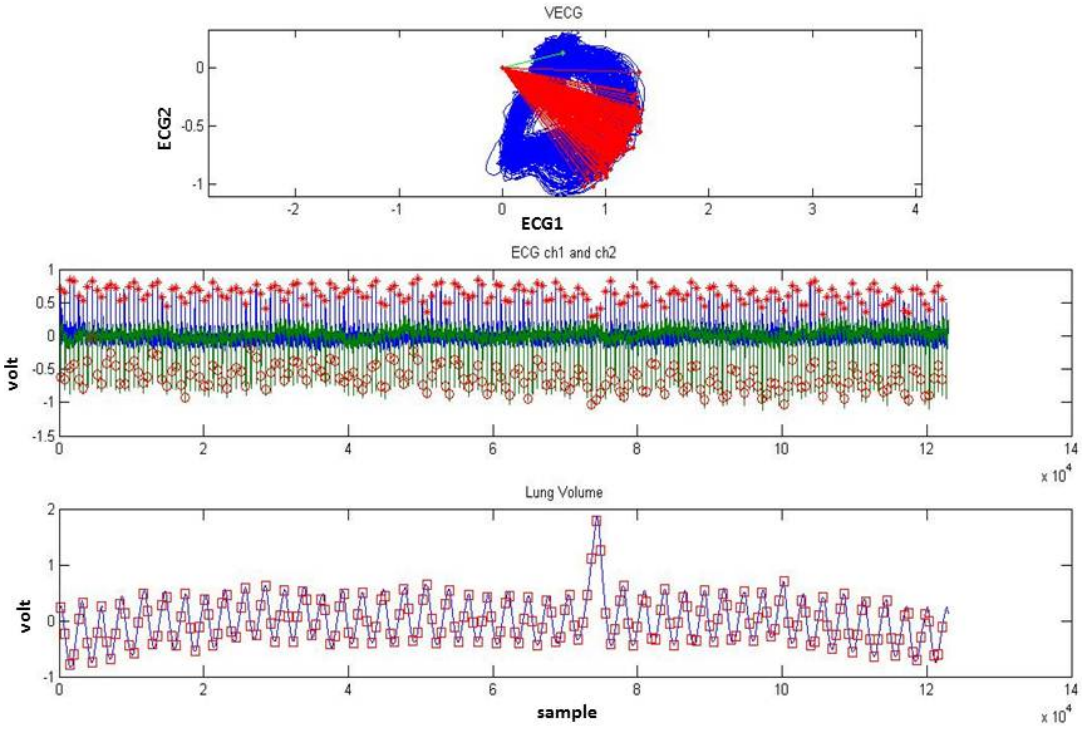

Figure 13: Max elongation lines and their instances in the ECG and Lung volume signals

6.2.3 Blind Source Separation (BSS): [1]

Blind source separation is a concept that is widely used in biomedical signal processing. BSS is used for signal extraction when the signal at hand contains the desired signal as well as some interference. The desired signal is generated from sources with overlapping time frequency spectra. BSS treats the signal at a certain time as a linear mixture of contributions from the different sources with different powers. The following equations describe the BSS system model:

□□=□□□□=□□ℎ□□□□(□)

□□=□1□,□2□,…..,□□□□

5)

Where $x(t)$ is the observed signal mixture, A is the mixing matrix with h_{ij} of size $n \times m$, which represents the projection of source j on observation i. $s(t)$ are the source signals with zero mean.

The word blind in BSS comes from the fact that only little or no information is available about the source signal $s(t)$ or the projection mixing matrix A. This makes BSS a very powerful and robust tool for applications where only the observation vector is known with almost no prior knowledge of the sources or their projection.

In order to get an estimate $\hat{S}$ of the source a matrix W needs to be calculated such that

6)

Columns of W is a spatial filter to estimate a single source of S

7)

This problem as is stated is an ill posed problem. To be able to find a solution, the sources have to have certain properties such as mutual statistical independence, non-Gaussian distribution, distinct frequency spectra, or known discrete support.

Heart beats can be considered as independent, and therefore, with respect to this assumption, the separation of sources is applicable.

6.2.4 Principle Component Analysis (PCA):

Assuming independence of sources principle component analysis is widely used in biomedical application to perform the blind separation of sources. Given observations X(t), the PCA maximizes the second moment of $\hat{s}$ defined as $\hat{s}$ by locating orthogonal axes also named the principle components (PCs) that span the space of matrix H.

8)

9)

Geometrically PCA can be understood in the following way: if we have matrix H (the mixing matrix), then the image of a unit sphere under matrix H is a hyper ellipse (ellipsoid in more than 3 dimensions) [10]. So, a matrix H rotates and stretches the unit sphere. PCA can be understood from this geometric interpretation as a method to indicate the new rotated coordinates, and it gives scores to each coordinate according to its variance or power. For example, figure 14 shows the original sphere and its image after rotation and stretching. The PCA will indicate these new coordinates after transformation by matrix H and will assign more power to the coordinate along which the ellipse stretches more.

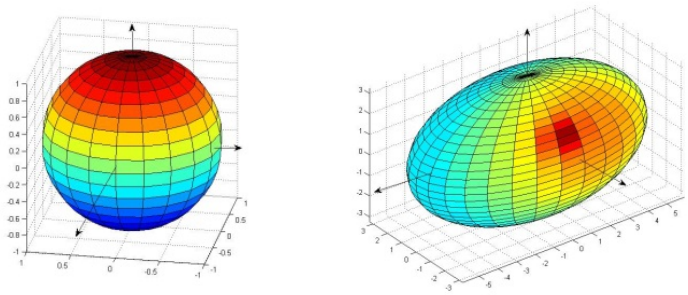

Figure 14: Unit Sphere Image under arbitrary matrix A

Therefore, PCA represents a spatial filter by estimating □□ orthogonal to {□*1* □*2*……□□*−1*} .These orthogonal vectors represent the transformed space under H.

Applying this concept to signals, PCA is a tool to identify components of a signal. It treats the signal as a vector in the signal space and tries to determine an orthogonal basis that spans this signal space. This is equivalent to de-correlating the signal by projecting the data on to its orthogonal axes [8].

By extracting the components of the signal the sub-procedures of the signal can be identified. In addition, by finding the singular values representing the power at each orthogonal axis – or, in geometry, the stretching of the ellipse – the components of the signal can be ranked according to their power. That is the reason why the PCA can be used to de-noise signals since the noise has normally less power than the signal as shown in figure 15 and 16 [8].

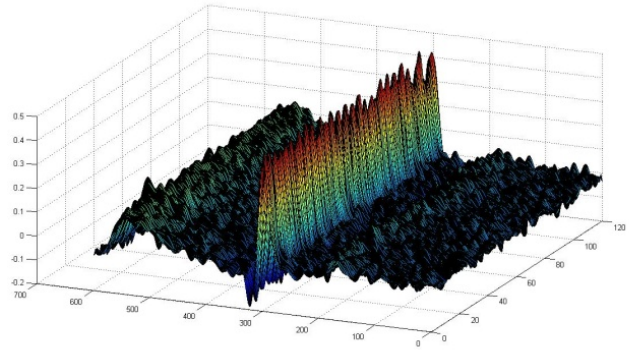

Figure 15: noisy ECG pulses

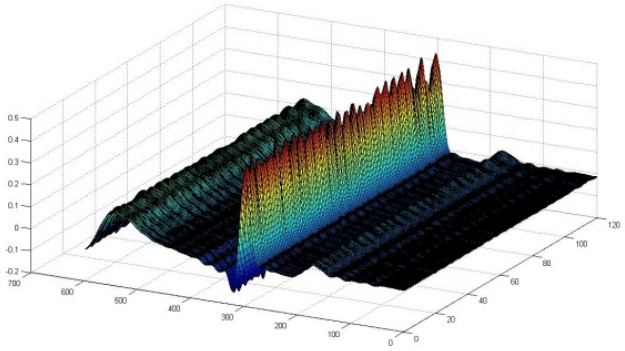

Figure 16: Reconstruction of ECG using the 1 dominant PC

The principle components (PCs) of a signal can be obtained by a method called singular value decomposition. Consider a signal contained in the form of the real matrix $A_{m \times n}$ where

$$A_{m \times n} = U_{m \times m} \; S_{m \times n} \; V^*_{n \times n} \quad (10)$$

V is columns of the Eigen vectors of X*X representing the orthogonal space of X and U is the Principal Components (PCs) of X or the projection of X on to the orthogonal space or the new rotated orthogonal vectors of the ellipse. S is a matrix that has singular values of X on its diagonal axis and zeros elsewhere. To reconstruct X from the PCs, equation 10 can be used.

However, if only few PCs are considered in order to de-noise the signal the following identity needs to be used:

$$\square = \square \square\square\square *$$

11)

There $\square\square$ is the diagonal matrix of the singular values of the selected PCs and zero elsewhere [1].

This decomposition can be carried out also, by evaluating the Eigen values and vectors of the covariance matrix of X, arranging them in order from the highest Eigen value to the lowest corresponding to the pattern or the base with the variance or highest power, respectively. Then, the signal is projected onto the basis to obtain the PCs calculating the dot product of X and the Eigen vectors [13]. With

12)

Then the following Eigen value equation is formed:

13)

Where v_j is the Eigen vector and λ_j is the corresponding Eigen value. Then the PCs can be obtained by dot product

14)

Where $\square\square$ are the components of the principle component vector and X is the original data matrix [13]. A very convenient method to evaluate the PCs is to use the Matlab embedded function SVD.

PCA was used in our analysis to indicate which principle component is sensitive to variations of the lung volume and lung pressure. By knowing these PCs we can eliminate all the others and have better correlation with lung volume and lung pressure using only the significant PCs and regarding all the others as noise. To obtain the orthogonal basis of the ECG signal, the data matrix X is first constructed from the ECG signal as before by widowing the pulses. Then, by using the SVD embedded function, the PCs were evaluated. There are as many PCs as there are pulses. Most of them show only small significance as the first 3 PCs describe more than 95% of the signal's variance and most of signal power.

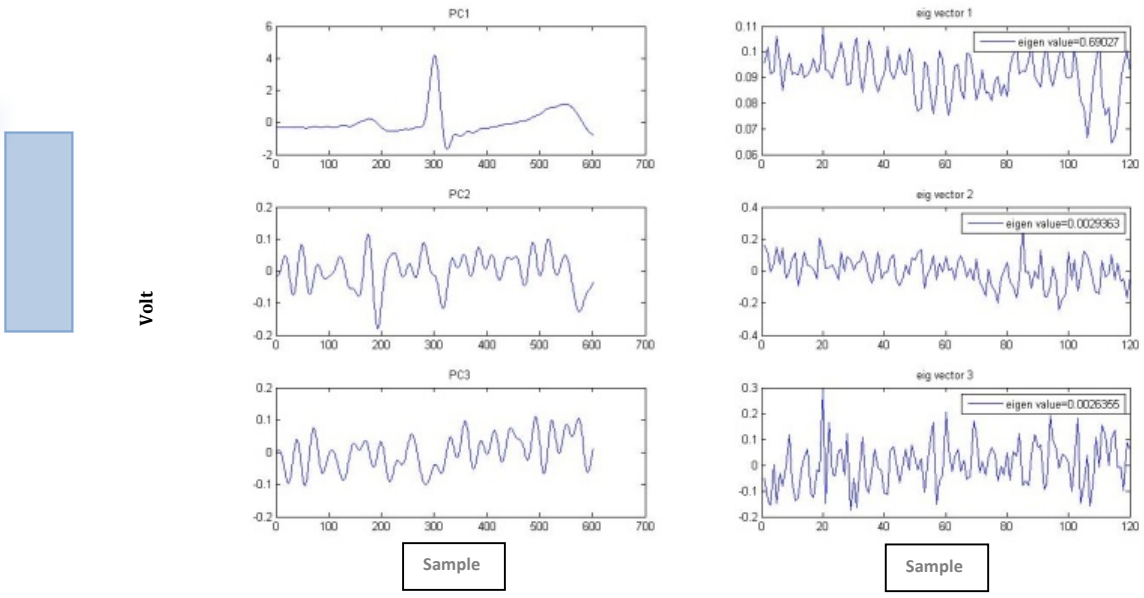

Figure 17: dominant 3 PCs and their corresponding Eigen vectors

7 Measurements and Results:

ECG features were extracted and correlated with lung volume and lung pressure to examine the effect of respiration on the ECG signal. The features extracted were R-Peak to the base line and R-Speak, which is the distance from R to S point. Also, area features was calculated and correlated with lung volume and lung pressure at the R time instance. These features were PulseArea, which is the area of the whole pulse, Q-RArea the area from the beginning of the pulse until R point, R-SArea the area from the R time instance to the end of the pulse, the RatioArea of the front to end area is also calculated and Q-SArea that is the area from the Q to S time instances. In addition, VECG features were also extracted such as elongation, angle and area of the VECG loop and the correlation with lung volume and pressure evaluated.

The correlation used in the study is calculated using the normalized cross correlation calculated by subtracting the means of the two entities and dividing by the norm of both as shown in the following equation:

15)

Where x and y are column vectors and T is the transpose operation of the vectors.

The scattering error is calculated as the standard deviation of the points at scattering plots (see Appendix 2) from the best-fit straight line.

7.1 Lung Volume:

From the pool of 8 subjects, normal respiration air flow and ECG signals were recorded and lung volume was calculated by integrating the flow signal. ECG features were extracted from the ECG signal and correlated with lung volume at the R-Peak time instance.

7.1.1 Correlation of R-peak and R-SPeak with lung volume

The first feature extracted from the ECG signal is the R-Peak. At the instance of the R-peak, the signal record of the lung volume is marked to enable correlation between lung volume and ECG signal as shown in the following figure.

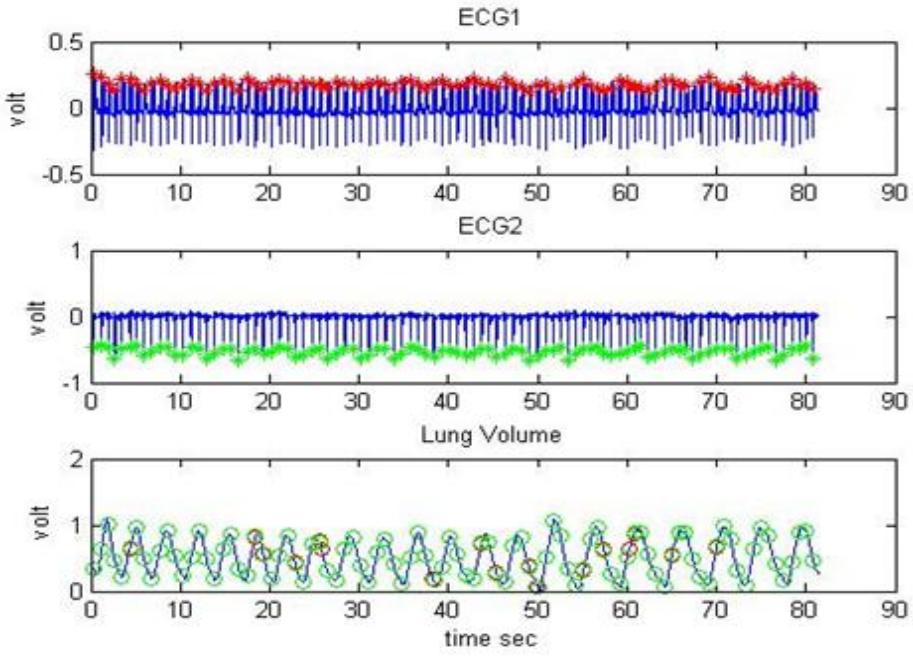

Figure 18: Lung Volume instances at the R-Peak of Each channel of the ECG

(Appendix 2) shows a scatter plot of the R-peak versus the lung volume of the 8 subjects. There is a clear correlation between the two signals and this

correlation increases as the subjects breathed deeper. The correlation was calculated separately for each ECG channel.

All comparisons are done vs. the value of the lung volume marked at the R-Peak time instant.

Table 1: Correlation Results for R peak Ch1 and ch2

Subject	R-Peak1		R-Peak2		R-Speak1		RS-Peak2	
	corr	error	corr	error	corr	error	corr	error
1	**-0.74**	0.579	**0.701**	0.629	**-0.65**	0.617	**0.741**	0.658
2	**-0.92**	0.878	**0.743**	0.924	**-0.92**	0.692	**0.764**	0.843
3	**-0.86**	0.565	**0.639**	1.076	**-0.87**	0.417	**0.802**	0.776
4	**-0.57**	0.718	**-0.06**	0.345	**-0.76**	0.467	**0.35**	0.384
5	**-0.89**	1.017	**0.498**	0.763	**-0.9**	0.88	**0.281**	0.884
6	**-0.27**	1.102	**-0.62**	0.759	**-0.06**	0.973	**-0.61**	0.811
7	**-0.86**	0.945	**0.662**	0.917	**-0.92**	0.796	**0.873**	0.694
8	**-0.64**	0.894	**0.539**	1.718	**0.477**	0.76	**0.077**	2.803
Avg	**0.7188**	0.8373	**0.5577**	0.8914	**0.6946**	0.7003	**0.5623**	0.9816

Table 1 shows the correlation obtained for R-Peak and R-Speak with lung volume. Most of the subjects show some correlation between the R-Peak and lung volume. In most cases, the height of the R-Peak decreases as the lung volume increases. This tendency is larger in case of the ECG1 that spans the left and right arms than the ECG2 from left arm to left leg. This is because ECG1 spans chest more than ECG2 and hence it is affected more by chest movement and change in lung volume.

The normal R-Peak to base line was found to have a better correlation with the lung volume than the R-SPeak. The average correlation for the R-Peak was 72% while for the R-SPeak it was 69%.

7.1.2 ECG Area Features Correlation with Lung Volume:

The second feature examined from the ECG is the PulseArea and it is calculated by integrating the whole beat (see Appendix 1). Also, the Q-SArea is calculated and correlated with the lung volume.

As shown in table 2 the PulseArea showed little correlation with lung volume with an average correlation of 51% and a scattering error of 0.81%. However, the correlation was higher in the Q-SArea that is calculated from the Q to S point with a correlation of 71% and a scattering error of 0.86%. The area feature as well as the R-peak showed better correlation with the first ECG channel and they had more or less similar correlation and scattering.

Table 2: correlation of ECG area with lung volume

Subj	**PulseArea1**		**PulseArea2**		**Q-SArea1**		**Q-SArea2**	
	corr	**error**	**corr**	**error**	**corr**	**error**	**corr**	**Error**
1	**-0.6**	0.407	**0.74**	0.607	**-0.7**	0.621	**-0.7**	0.602

2	**-0.9**	0.613	**0.46**	0.951	**-0.9**	0.889	**-0.9**	0.898
3	**-0.5**	0.65	**0.49**	1.21	**-0.8**	0.475	**-0.8**	1.158
4	**-0.5**	0.703	**0.38**	0.93	**-0.7**	0.541	**-0.7**	0.42
5	**-0.7**	1.11	**0.18**	0.853	**-0.9**	1.151	**-0.9**	0.81
6	**-0.1**	0.519	**-0.4**	0.88	**-0.2**	1.371	**0**	0.802
7	**-0.3**	1.729	**0.51**	1.136	**-0.8**	1.003	**-0.8**	0.824
8	**0.45**	0.804	**-0.2**	1.296	**-0.7**	0.829	**0.47**	1.866
Avg	**0.5062**	0.8169	**0.42**	0.9829	**0.7125**	0.86	**0.6588**	0.9225

The other derived area features Q-RArea, R-SArea and their RatioArea were calculated and examined.

Most of extracted QRS features showed poor correlation with lung volume as shown in table 3.

Table 3: Correlation QRS special features with lung volume

Subj	Q-RArea1		Q-RArea2		R-SArea1		R-SArea2		RatioArea1		RatioArea2	
	corr	error	corr	error	corr	error	corr	error	corr	error	corr	error
1	**-0.34**	0.621	**0.66**	0.714	**-0.62**	0.401	**0.71**	0.686	**0.22**	0.622	**-0.05**	0.74
2	**-0.78**	1.034	**0.63**	1.289	**-0.92**	0.602	**0.04**	1.201	**-0.02**	1.054	**0.45**	1.545

3	**-0.12**	1.288	**0.53**	1.353	**-0.54**	0.615	**0.36**	1.338	**0.24**	1.191	**0.02**	1.447
4	**-0.47**	1.127	**0.37**	1.122	**-0.32**	0.518	**0.35**	0.825	**-0.4**	1.078	**0.2**	0.787
5	**-0.48**	1.664	**-0.06**	1.056	**-0.8**	0.825	**0.4**	0.927	**-0.08**	1.694	**-0.42**	1.004
6	**0.29**	1.032	**-0.43**	1.051	**-0.65**	0.679	**-0.3**	0.889	**0.51**	1.108	**-0.19**	1.11
7	**-0.24**	2.036	**0.38**	1.384	**-0.28**	1.776	**0.57**	1.149	**0.05**	1.831	**-0**	1.103
8	**0.44**	1.391	**-0.06**	1.493	**-0.44**	0.884	**-0.17**	2.022	**-0.11**	1.474	**0.04**	1.912
avg	**0.3950**	**1.274**	**0.390**	**1.1828**	**0.5713**	**0.7875**	**0.363**	**1.1296**	**0.204**	**1.2565**	**0.171**	**1.2060**

7.1.3 VECG features correlation with lung volume:

Another method investigated was the VECG (see section 6.2.2). The maximum elongation line is detected and the corresponding instant at the lung volume is indicated as shown in figure 19. Three features, VECG elongation distance, angle and VECG area were calculated and compared to the lung volume . The VECG is plotted and different parameters were extracted from it. In many cases at least one of the three features from the VECG showed good correlation with the lung volume. However, it did not reach values as high as the ones obtained with the R-peak. This can be due to the difficulty in extracting accurate VECG features because of their irregular shapes. However, our observation showed that in some cases the VECG changes its elongation as a function of the lung volume change while keeping its angle. In

other cases the VECG was swinging up and down changing its angle while keeping its elongation. In some cases, both features changed at the same time. That's why for each single feature the average correlation was rather low. Despite that, at least one of VECG features showed good correlation per subject.

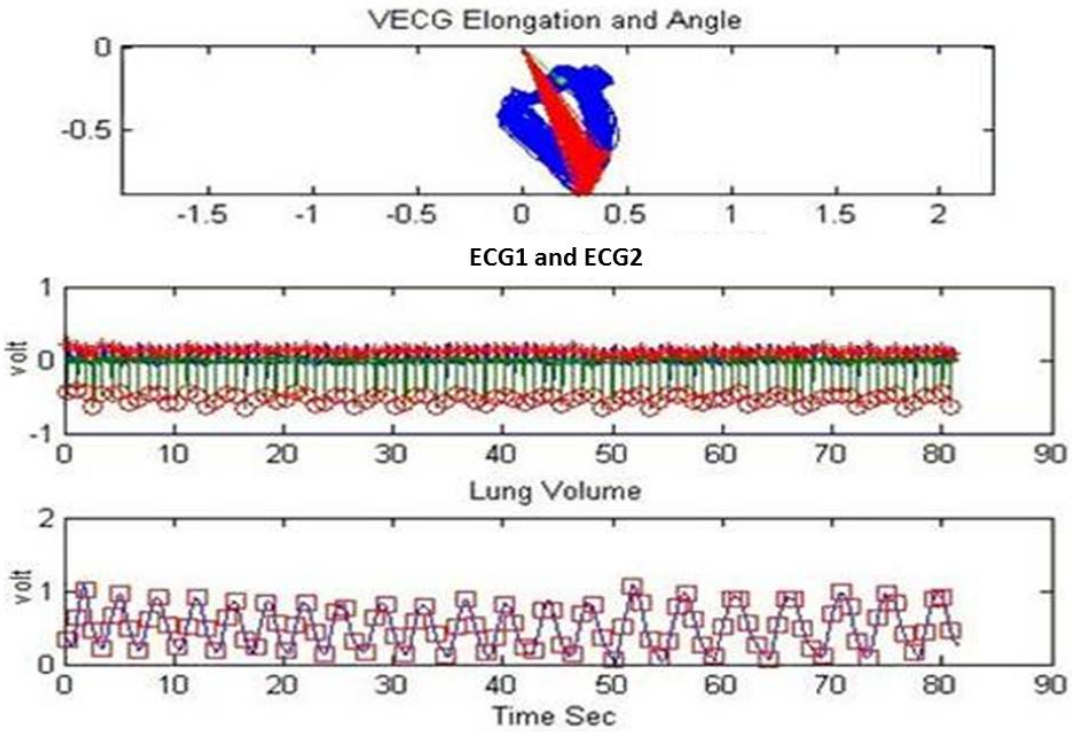

Figure 19: VECG plot with max lines marked

Therefore, if the VECG features are treated collectively and the feature with the highest correlation per subject is considered an average correlation of around 70% is obtained (see table 4).

Table 4: Correlation of VECG with lung volume

Subj	VECG Elongation	VECG Angle	VECG area

	corr	error	corr	error	corr	Error
1	**0.52**	0.239	**0.74**	0.456	**0.07**	1.786
2	**0.02**	1.493	**0.84**	2.197	**-0.89**	0.47
3	**0.2**	2.702	**0.25**	1.694	**0.48**	0.726
4	**0.16**	2.995	**0.09**	1.846	**-0.64**	0.742
5	**-0.01**	2.886	**0.19**	1.772	**-0.55**	2.364
6	**-0.66**	0.473	**-0.33**	0.405	**-0.66**	1.313
7	**0.14**	0.786	**0.83**	0.613	**-0.46**	1.439
8	**0.09**	2.664	**-0.13**	2.823	**-0.78**	2.447
avg	**0.2250**	**1.7798**	**0.4250**	**1.4757**	**0.5663**	**1.4109**

7.1.4 Using principal component analysis (PCA) to enhance correlation:

In order to enhance the correlation, PCA has been applied to reconstruct the R-Peaks first and then correlate them with the lung volume. One PC is used to reconstruct the ECG signal because most of the signal's variance (app. 95%) is explained by the first PC, and the 1st PC has most of the signal's power. As shown in the following figure, the first PC has singular value of 0.98 while the next closest PC has a singular value only 0.005. This means the 1st PC has much more power than the closest PC in the ECG signal.

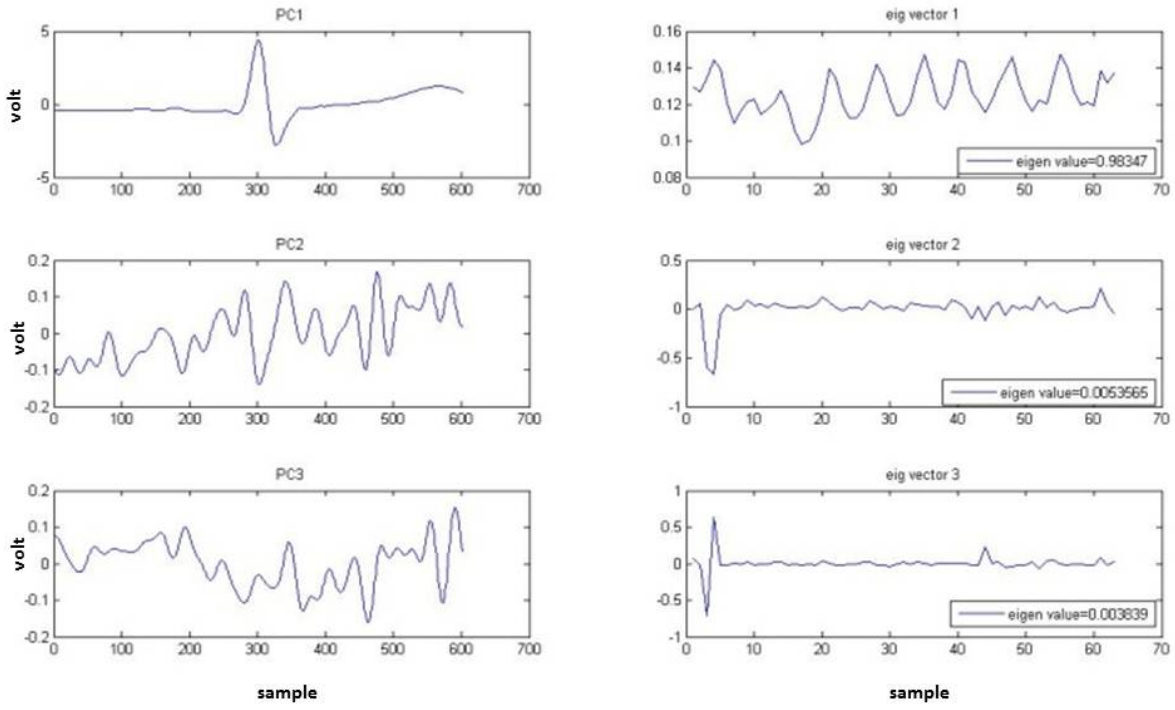

Figure 20: first 3 PCs along with their Eigen vectors and singular values

The following figure shows the normal R-Peak to base line with a red circle along with the constructed R-peak using PCA marked with a green star.

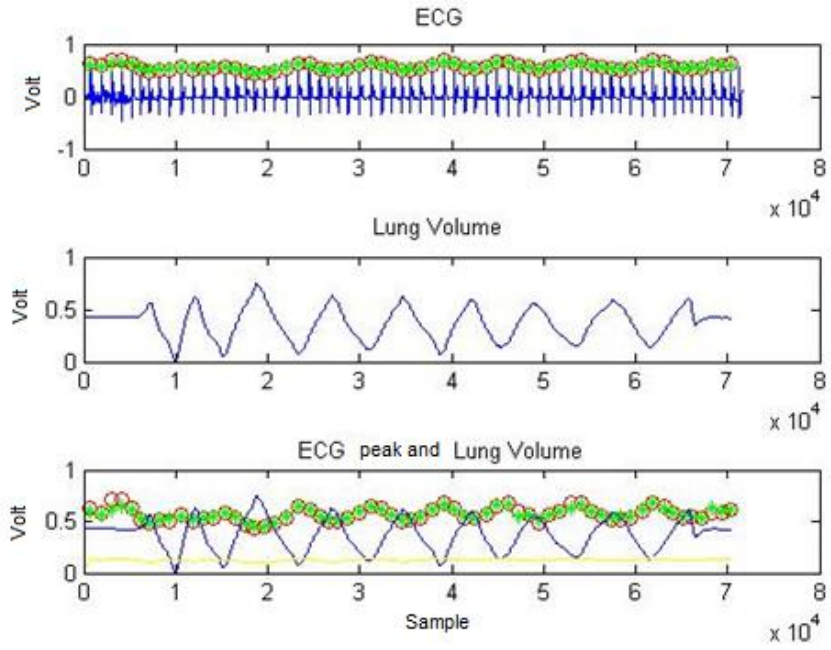

Figure 21: constructed R-Peak Using PCA

The following figures are comparing the constructed R-peak using the first PC and correlating the outcome with lung volume at the R-peak instance.

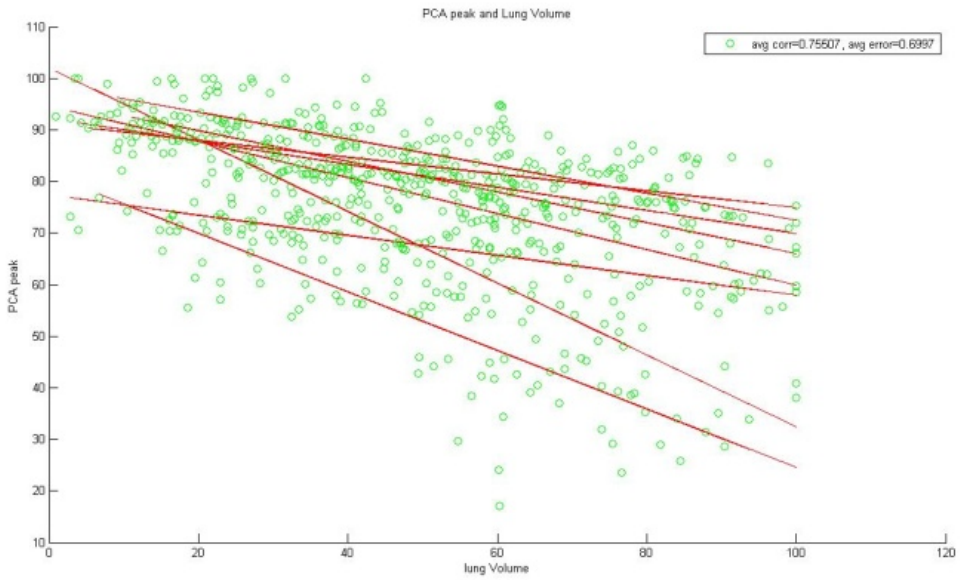

Figure 22: Correlation of PCA constructed R-Peak and Lung Volume of ECG1

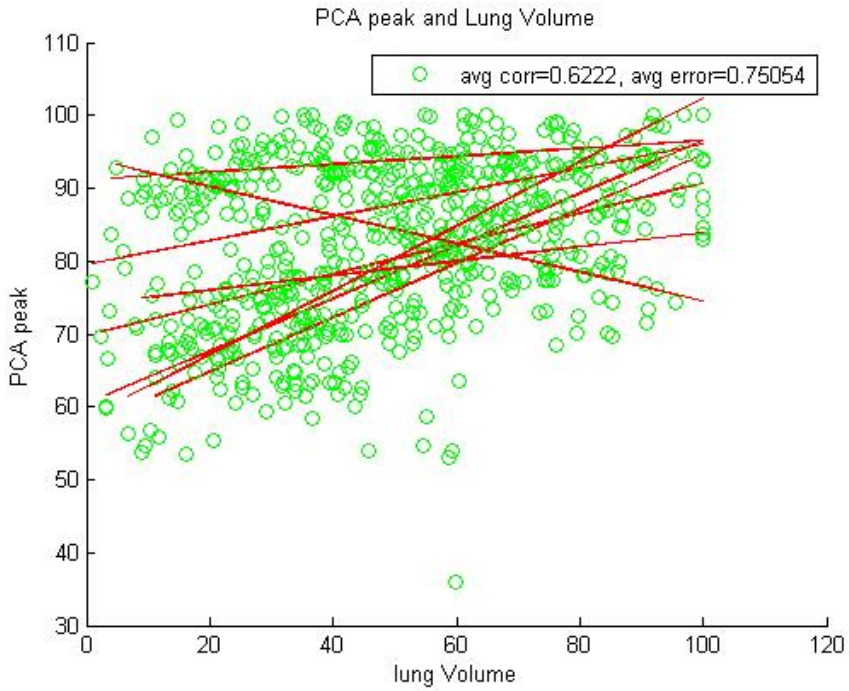

Figure 23: Correlation of PCA constructed R-Peak and Lung Volume of ECG2

The PCA constructed R-Peak for ECG1 was found to have a better correlation than the normal R-Peak by 5.38% and its scattering was reduced by 16.44% (see Table 5).

Table 5: PCA constructed with 1 PC R peak correlation with lung volume

Subj	Rpeak1 PCA1		Rpeak2 PCA1	
	corr	error	corr	error
1	-0.743	0.4739	0.742	0.5959
2	-0.925	0.6942	0.786	0.7998
3	-0.748	0.4748	0.878	5.43E-01
4	-0.781	0.3817	0.367	2.92E-01
5	-0.894	0.8644	0.471	0.7619
6	-0.39	1.0536	-0.717	5.19E-01
7	-0.844	0.9596	0.866	0.6809
8	-0.716	0.6954	0.152	1.8123
avg	0.7551	0.6997	0.6224	0.7506

7.2 Central Apnea Simulation:

To examine the effect of respiration on the ECG even more, an experiment that involves instances of breathing and holding breath is performed.

The experiment that is used to simulate the central apnea consists of a normal breathing period of 60 s followed by a period from 40s to 120s where the subjects are holding breath and repeating this procedure 4 to 5 times. Refer to Figure 24. As shown in the figure, the left side is the first 3 PCs and the left side is their corresponding Eigen vectors.

A comparable correlation to the lung volume change is noticed.

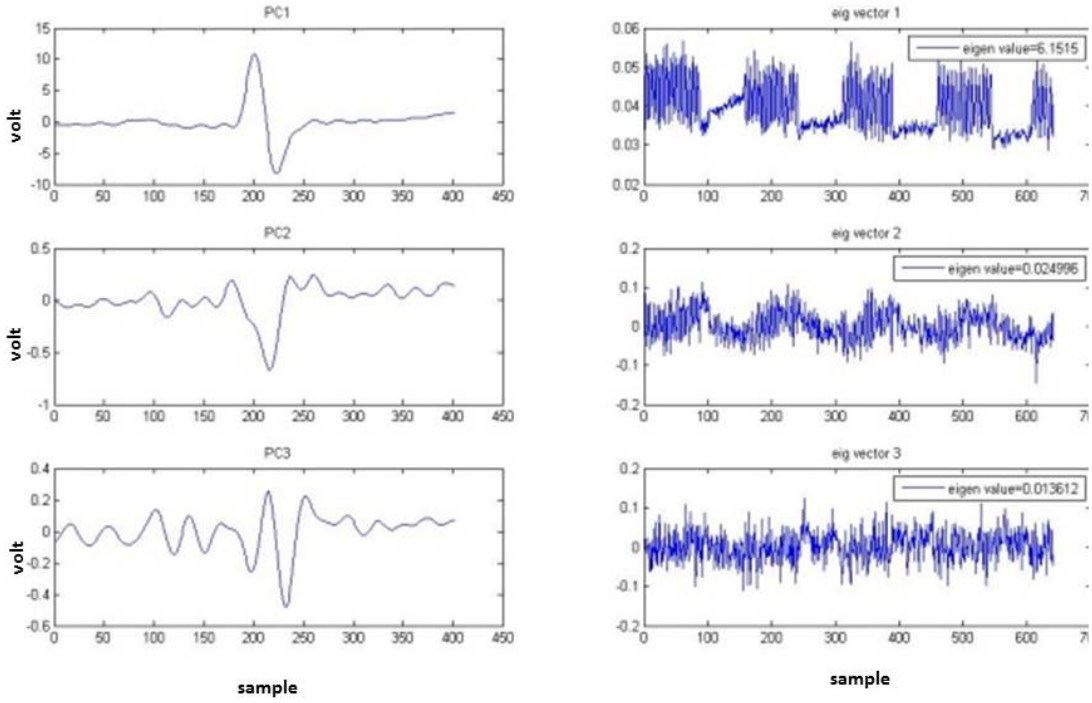

Figure 24: Most significant 3 PCs with their Eigen vectors

Moreover, a flat pattern on the Eigen vectors was noticed. This was most significant on the first Eigen vector followed by the second, and it indicates the times of normal respiration and breathing stop. Therefore, the Eigen vectors

can be used to indicate the event of an apnea. Figure 25 shows the first 3 Eigen vectors as a function of the lung volume. The simulated apnea events are clearly indicated by the first Eigen vector (Eig Vector1).

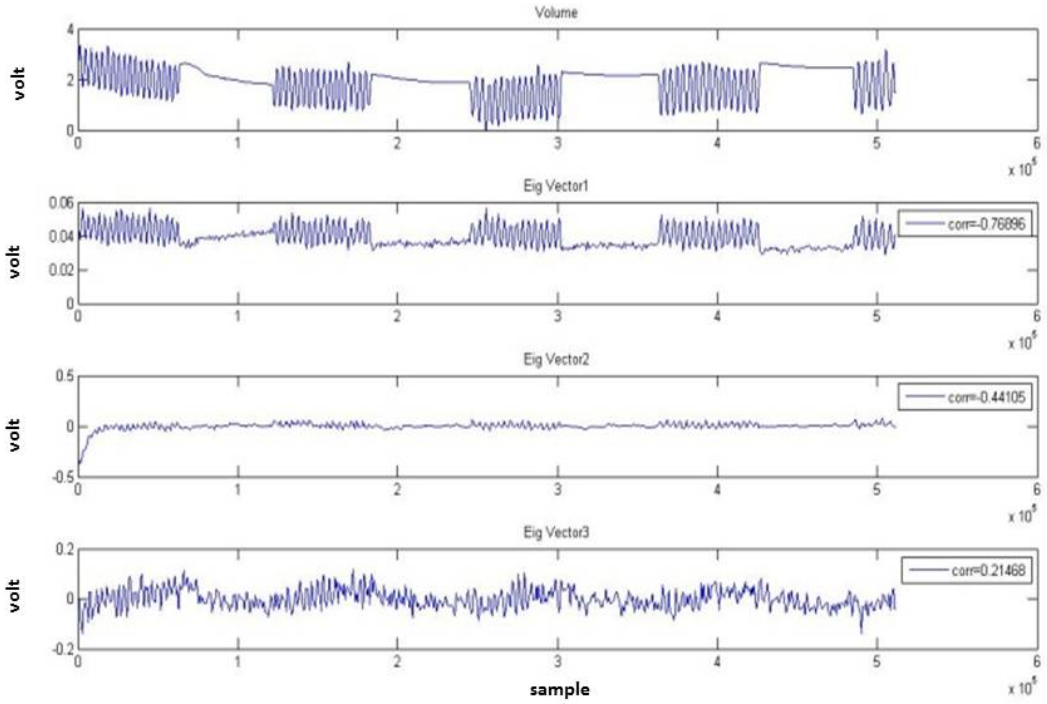

Figure 25: Lung Volume and the most significant 3 Eigen vectors

The dependence of the Eigen vectors on the lung volume was noticed in all simulated cases. Therefore, this method was applied to real apnea measurements. The signals with different types of apnea were taken from the internet (http://www.physionet.org/). The pattern (Figure 26) was noticed too on the real apnea data; however it has less flattening than the simulated case because the simulated case is very ideal.

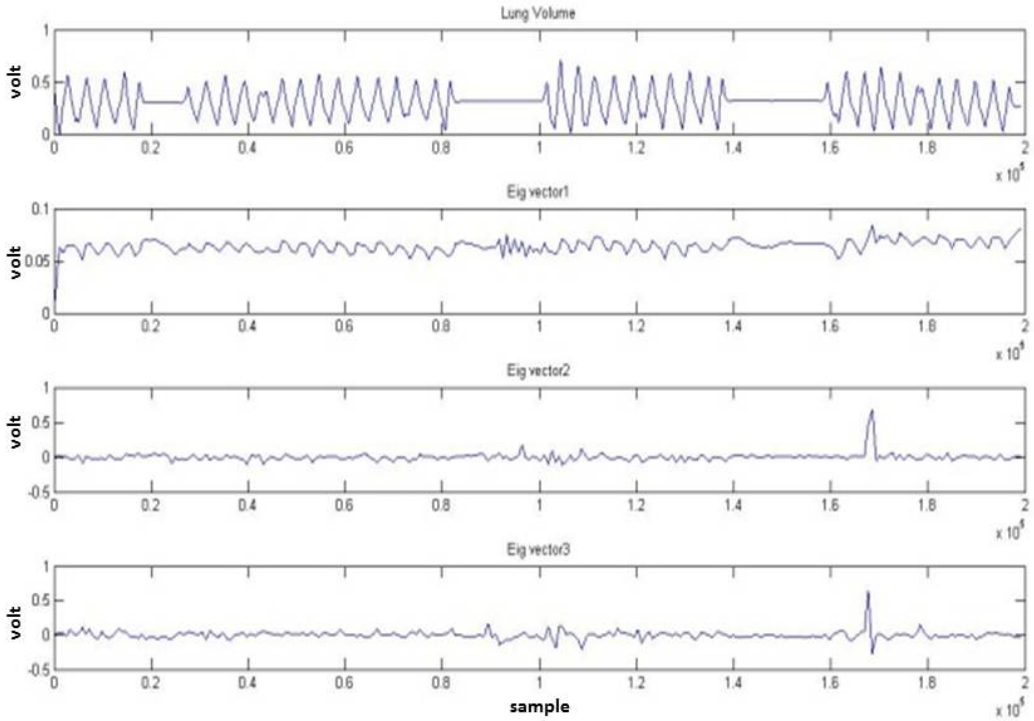

Figure 26: Lung Volume and first 3 Eigen vectors in real apnea case.

7.3 Summary of lung volume results:

The lung volume was recorded for 8 subjects simultaneously with ECG1 and ECG2. In general, the lung volume was found to have better correlation with ECG1 channel extending from the left to the right arm. The reason for this is that it spans more of the chest than the ECG2 hence it is more susceptible to changes from chest movement.

The R-Peak and Q-SArea features were found to have good correlation, while features extracted from the QRS complex, such as Q-RArea and R-SArea, seemed to have little correlation with lung volume. The VECG showed low correlation for the elongation, angle and area of VECG loop. Though at least

one feature of VECG was found to have some correlation per subject. The R-Peak constructed using PCA has proven to have the best correlation with the lung volume. Moreover, PCA Eigen vectors showed flat patterns at instances of breath hold.

7.4 Lung Pressure Result:

In this section we report on the correlation of the ECG signal features (see section 6) and the lung pressure. The lung pressure experiments were performed by making the subjects produce a continuously increasing pressure in the lungs and recording the ECG signal at the same time as shown in figure 27.

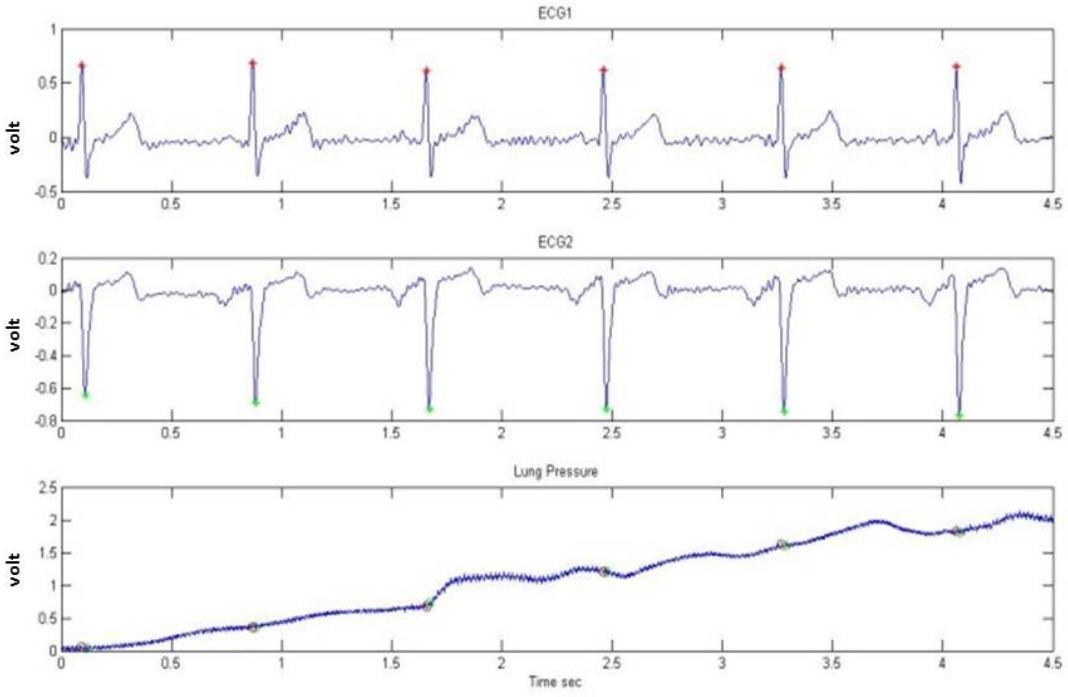

Figure 27: Increasing lung pressure while measuring 2 channels ECG

The pressure experiment was repeated at 5 different lung volumes to see if the lung volume is affecting the ECG.

7.4.1 Correlation of R-peak and R-SPeak with lung Pressure:

The 1st feature extracted from the ECG1 and ECG2 signals is the R-Peak. The R-Peak time instance is marked and the corresponding value of the pressure is saved. Figures 59-63 in Appendix 2 show the R-Peaks of the two ECG channels as a function of the lung pressure.

The R-Peaks showed good correlation with the lung pressure (table 6) especially in case of ECG2, which had an average correlation of 79% with a scattering error of 1.7.

Table 6: R-Peak correlation with lung pressure for 5 lung volumes

lung volume	**R-Peak1**		**R-Peak2**	
	corr	Error	corr	error
1	0.60491	1.3144	0.72075	1.4137
2	0.55666	2.6549	0.74926	1.8457
3	0.6126	2.6918	0.70496	1.9233
4	0.39482	2.8874	0.85023	1.614
5	0.56782	5.0543	0.90459	1.7357
average	**0.547362**	**2.92056**	**0.785958**	**1.70648**

(R-SPeak), the peak from R to S point, showed the maximum correlation with lung pressure. From the correlation figures (Appendix 2) and Table 7, the average correlation of this feature with the lung pressure was 81% and the

average scattering error was 1.56 (table 7). The R-SPeak correlation is found to have better correlation than the normal R-Peak. This indicates that not only the R-Peak is affected by lung pressure variation but also the S point is shifted.

Table 7: R-SPeak correlation with lung pressure for 5 lung volumes

lung volume	R-SPeak1		R-SPeak2	
	corr	error	Corr	error
1	0.5602	1.263	0.72119	1.5175
2	0.44724	2.0658	0.8552	1.3637
3	0.78678	1.6668	0.72624	1.616
4	0.54271	2.5648	0.86868	1.5772
5	0.71312	2.5352	0.89815	1.7269
avg	0.61001	2.01912	0.813892	1.56026

7.4.2 Correlation of ECG area features with lung pressure

The PulseArea is calculated by integrating over the whole ECG beat assuming that the most significant area of the ECG signal is within the QRS complex and ignoring the P and T-wave areas relative to QRS area (Refer to appendix1 for the definition).

The PulseArea is found to correlate with the lung pressure with 78% and showed a scattering of 1.3. As before the ECG2 showed a higher correlation with lung pressure than the ECG1 as shown in table 8.

Table 8: PulseArea correlation with pressure for 5 lung volumes

Lung volume	PulseArea1		PulseArea2	
	corr	error	corr	Error
1	0.44901	1.6332	0.68326	1.3505
2	0.41677	2.1856	0.88786	1.4327
3	0.63619	2.8516	0.78568	1.2347
4	0.47475	2.8743	0.81152	1.1581
5	0.39784	3.4927	0.75428	1.35
avg	0.474912	2.60748	0.78452	1.3052

The Q-SArea of ECG2 had a better correlation with the lung pressure (table 9) than the one of ECG1 with an average correlation of 69% and a scattering of 1.5, which is less than the PulseArea correlation. This indicates that the P and T waves areas included in the PulseArea are also affected by the lung pressure and hence making the correlation of PulseArea more than Q-SArea.

Table 9: Q-SArea correlation with lung pressure at 5 lung volumes

lung volume	Q-SArea1		Q-SArea2	
	corr	error	corr	Error
1	0.75136	1.2587	0.74207	1.491
2	0.62777	2.0238	0.6925	1.4271
3	0.79882	2.0172	0.78543	1.8782
4	0.48747	2.6682	0.44736	1.4627
5	0.61034	3.3438	0.78749	1.4817
avg	0.655152	2.26234	0.69097	1.54814

The Q-RArea is defined to be the area of the whole beat before the R-Peak (Refer to appendix 1 for the definition of Q-RArea).

The correlation of the Q-RArea was found to have a max correlation with ECG2 of 75% and a scattering of 1.7 as shown in table10.

Table 10: Q-RArea Front area correlation with pressure for 5 lung volumes

lung volume	Q-RArea1		Q-RArea2	
	corr	error	corr	error
1	0.49223	1.9333	0.69039	1.6449
2	0.62287	2.3394	0.85057	1.8264
3	0.54169	3.3943	0.79878	1.424
4	0.49251	3.8025	0.79112	1.3225
5	0.60094	3.5422	0.65489	2.4289
avg	0.550048	3.00234	0.75715	1.72934

The R-SArea is defined as the rest of the ECG beat after the front beat starting from the R-peak (Refer to section 6.2.1 and appendix 1).

From table11 R-SArea was found to have a max correlation of 63% with ECG2 and it shows a lower correlation than the Q-RArea. This indicates that the lung pressure has more impact on the section in front of the R-Peak of the ECG pulse.

Table 11: R-SArea end area correlation with pressure for 5 lung volumes

lung volume	R-SArea1		R-SArea2	
	Corr	error	Corr	error
1	0.48427	0.71627	0.46141	1.5724
2	0.50113	1.2032	0.78221	2.0355
3	0.71077	0.55777	0.64895	1.5929
4	0.49095	0.76698	0.73663	1.539
5	0.58104	1.6444	0.56994	2.0078
avg	0.553632	0.977724	0.639828	1.74952

The RatioArea area is computed by dividing the Q-RArea by the R-SArea (Refer to section 6.2.1 and appendix 1).

The scattering plots (Appendix 2) of the RatioArea vs. lung pressure were found to possess very scattered patterns. As can be seen in table 12, the RatioArea had very small correlation with the lung pressure indicating that the ratio of areas doesn't carry much information about the lung pressure.

Table 12: RatioArea front/end correlation with pressure for 5 lung volumes

lung volume	RatioArea1		RatioArea2	
	corr	error	corr	error
1	0.51044	1.9947	0.41698	1.8502
2	0.49768	2.3464	0.35475	2.8319
3	0.47069	3.4796	0.60428	1.9645
4	0.33627	3.8548	0.25117	1.8052
5	0.71439	3.1571	0.46344	2.7874
avg	0.505894	2.96652	0.418124	2.24784

In summary, in case of the single channel ECG the R-Speak, defined as the distance from the R-Peak to the S-point, was found to have the highest correlation with the lung pressure. Moreover, better correlation was found with ECG2, which extends from the left arm to the left leg. This may be because, upon application of pressure, the diaphragm (Fig. 5) exerts effort to overcome the closure, and the diaphragm lies more between the electrodes used to measure ECG2 than ECG1. (Refer to section 6.1 for the pressure experiments description).

The reliability of the method was tested by repeating the experiment on 2 subjects but only for one constant value of the lung volume (table 13). 20 measurements were taken per subject, and one subject showed a correlation of 70% with the R-Peak 2 while the other subject showed poor correlation (Refer to section 6.1 for the experiment description). This indicates that more tests need to be conducted in order to confirm the results and draw reliable conclusions.

Table 13: lung pressure correlation with ECG1 at a constant lung volume

Subj	R-peak1	R-SPeak1	Pulse area1	Q-S area1
1	0.569548	-0.85508	-0.06315	-0.40968
	0.532275	-0.60617	-0.59791	0.499098
	-0.96404	-0.19378	-0.00597	-0.83976
	-0.81961	-0.53509	0.796311	-0.31972
	-0.97019	-0.72262	0.671969	-0.35489
	0.057787	-0.53244	0.133369	0.525657
	-0.64529	-0.4472	-0.7057	-0.84635
	-0.43659	-0.4179	0.252797	-0.68224
	-0.58235	-0.46254	0.475304	-0.91898
	-0.56635	-0.4567	0.549726	-0.10691
	-0.89375	-0.62884	-0.47166	-0.70577
	0.587779	-0.00724	-0.9806	0.364088
	-0.76885	0.075076	-0.42616	-0.8755
	-0.44657	-0.66526	-0.21875	-0.41435
	-0.99106	-0.92923	-0.38989	-0.89427
	-0.6598	-0.62087	-0.78749	-0.89099
	0.524888	-0.42126	-0.55923	-0.42998
	-0.58575	0.397154	-0.59316	-0.23707
	-0.86236	0.22637	-0.96932	-0.85125
	0.538713	-0.84721	-0.04981	-0.26773

average	**0.6502**	**0.5024**	**0.4849**	**0.5717**
2	0.849581	0.881884	-0.09568	0.959457
	0.131075	-0.24315	-0.66295	-0.38737
	-0.21378	-0.08429	-0.5851	-0.16764
	-0.45187	0.375326	-0.65111	-0.18682
	-0.08997	-0.41019	-0.30125	0.057598
	0.777706	0.623868	-0.86781	0.447605
	0.741937	0.675913	-0.72917	0.783006
	0.395974	0.144467	-0.55343	0.288827
	-0.16256	-0.23874	-0.7552	-0.1102
	0.746148	0.946516	-0.5269	0.959929
	0.77128	0.825085	0.073945	0.819871
	0.4721	0.516907	-0.58989	0.429455
	0.480093	0.952469	0.291937	0.540371
	0.165386	0.799818	-0.54733	-0.22797
	-0.44209	0.926864	-0.70513	-0.31704
	-0.28555	0.868037	-0.81459	-0.17806
	0.501527	0.914648	0.024053	0.710672
	0.559342	0.660994	0.578001	0.618659
	0.637976	0.452383	0.59138	0.650207
	0.913329	-0.7567	0.927234	0.914879
average	**0.4895**	**0.6149**	**0.5436**	**0.4878**

Table 14: lung pressure correlation with ECG2 at a constant lung volume

Subj	R-Peak2	R-SPeak2	Pulse area2	Q-S area2
1	0.23509	0.640643	0.84276	-0.1254
	-0.27684	0.446243	-0.09337	-0.59837
	-0.75611	-0.32056	0.386605	0.359583
	-0.77282	0.223477	0.735908	0.829507
	-0.27192	0.462097	0.787666	0.80189
	0.741011	0.736295	-0.7932	-0.50418

	-0.94251	0.965265	0.810317	-0.3043
	-0.68705	-0.37167	0.312814	0.398263
	-0.49735	0.450359	0.623775	-0.27173
	0.20524	0.419903	0.424148	-0.21792
	-0.77548	0.635707	-0.18902	-0.58402
	-0.82767	0.22841	0.728231	0.819273
	-0.79543	0.51877	-0.07334	0.015766
	-0.27191	0.177081	0.827441	0.864797
	-0.40589	0.857866	0.889591	0.767958
	-0.3168	-0.08885	0.487702	0.663712
	0.699013	-0.28449	0.853144	0.528222
	-0.61521	-0.52638	0.432703	0.858698
	-0.75422	0.142978	0.764087	0.989485
	0.007232	0.60311	0.792863	-0.21447
average	**0.5427**	**0.455**	**0.5924**	**0.5359**
2	-0.63447	-0.53482	0.702163	0.386868
	-0.44964	0.864313	0.613467	0.29642
	-0.89155	0.445542	-0.13029	-0.8122
	-0.95141	0.454741	0.699233	-0.00465
	-0.76934	-0.37983	-0.4624	-0.90118
	-0.7569	0.710109	-0.42658	-0.37003
	-0.44057	0.846817	-0.76919	-0.37425
	-0.8642	0.553553	-0.24861	-0.88181
	0.212686	0.374998	0.229054	-0.29498
	-0.96814	0.423535	-0.56715	-0.28002
	-0.67931	-0.38309	-0.54529	0.13135
	-0.93281	0.4609	0.272938	-0.35868
	-0.90214	0.267619	0.27123	-0.69693
	-0.93034	0.526785	0.629925	-0.65954
	-0.68104	-0.40134	-0.56377	0.263397
	-0.96828	0.559902	0.700396	-0.1521
	-0.87658	0.165149	-0.61188	-0.65878

	-0.30055	0.345832	0.834431	0.743646
	-0.14251	0.053977	-0.76941	-0.53649
	-0.75961	0.540427	-0.44006	-0.37667
average	**0.7056**	**0.4647**	**0.5244**	**0.459**

7.4.3 Correlation of VECG with lung pressure:

In this section, relational analysis of two ECG channels (VECG) is conducted, and features such as VECG elongation length, angle and area (see 6.2.2) are extracted and correlated with the lung pressure values at the R-Peak. The following figure shows a VECG plot together with the ECG1 and ECG2 signals and the lung pressure. The values and instances of the max elongations of the VECG plot are marked with circles.

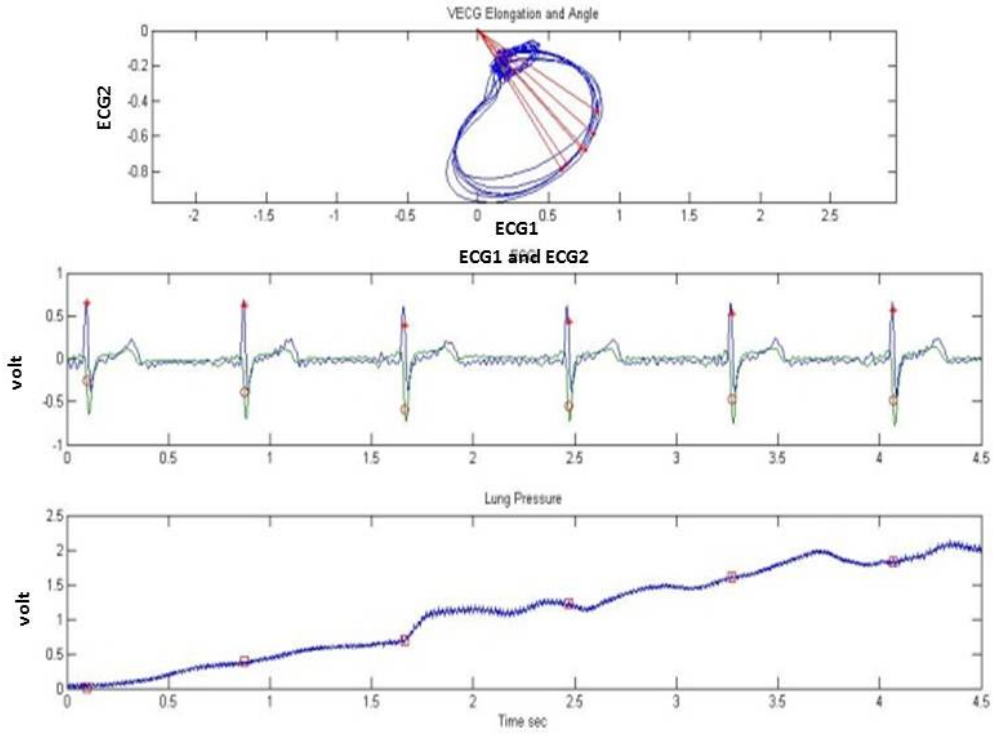

Figure 28: VECG and pressure

The first feature in the VECG is its elongation length defined as the max distance of the VECG curve from the zero point. The scattering plots of this feature can be found in Appendix 2.

The VECG elongation length showed very high scattering patterns of 5.3557 and its correlation of 55.63% on average with lung pressure was very weak. Table 15 includes average results of all subjects at each lung volume.

Table 15: VECG Elongation correlation with pressure for 5 lung volumes

lung volume	VECG Elongation	
	corr	error
1	0.5119	3.9787
2	0.5484	7.5388
3	0.4968	3.9196
4	0.6397	4.3287
5	0.5846	7.0127
average	0.5563	5.3557

The second feature considered is the VECG inclination angle with the positive x-axis. This inclination is defined as the angle between the max. line and the positive x-axis (Section 6.2.2). The correlation of the angle with lung pressure was found to be better than the one of the elongation length yet it is still low. The angle showed a correlation of 66% and a scattering error of 3.4237 (table 16).

Table 16: VECG angle correlation with pressure for 5 lung volumes

lung volume	VECG Angle	
	corr	error
1	0.5372	3.6539
2	0.6206	4.5615
3	0.7701	2.6515
4	0.7490	1.8072
5	0.6470	4.4443
average	0.6648	3.4237

The final feature extracted is the VECG area defined as the area enclosed by the VECG curve. The VECG area shows the best correlation out of the relational ECG features with a value of 78.7% and a scattering of 3.9 (table 17).

Table 17: VECG area correlation with pressure for 5 lung volumes

lung volume	VECG Area	
	corr	error
1	0.8845	2.0425
2	0.8033	4.5223
3	0.6602	3.8171
4	0.8055	4.5911
5	0.7790	4.9284
average	0.7865	3.9803

In general, the relational ECG was characterized by relatively low correlation compared to the single channel features. Also, the VECG features had larger scattering of the correlation than the single channel ECG features.

In conclusion, consistent results of the effect of the lung volume on the correlation of the VECG and the lung pressure were not found. In order to improve the results, we suggest to design a similar experiment and measure the pressure at a single value of the lung volume and repeat this measurement several times per subject. It would also be necessary to increase the number of subjects studied.

7.4.4 Using PCA to enhance the lung pressure signal:

The principle component analysis is applied to the lung pressure signal in order to reduce the noise before calculating the correlation between the R-peaks and the new lung pressure signal again. This did not yield a significant improvement since there were not enough PCs as the subjects could apply pressure for only a short time spanning just a few ECG pulses (section 6.1).

The Following table shows R-Peak2 constructed using the dominant PC and the results are compared with the original R-Peak2 and R-SPeak2. As can be seen, using principal component analysis didn’t enhance the correlation with lung pressure.

Table 18: correlation of PCA constructed R-Peak vs. original R-Peak and R-SPeak of ECG2

lung volume	R-Peak2 PCA1	R-Peak2	R-SPeak2
1	0.108609	0.745923	0.8069
	0.938293	-0.93457	-0.90174
	0.786932	-0.915	-0.82924
	0.559632	-0.46166	-0.35566
	-0.43405	0.380235	0.533264
	0.931712	-0.88714	-0.90036
avg	0.6265	0.7208	0.7212
2	0.977401	-0.90329	-0.69593
	0.969386	-0.9862	-0.99855
	0.122073	-0.11403	-0.87068
	0.887796	-0.86643	-0.83528
	0.641052	-0.64767	-0.76834
	0.98404	-0.97792	-0.96239
avg	0.7636	0.7493	0.8552
3	0.952478	-0.9186	-0.88669
	0.408169	-0.58289	-0.81616
	0.613785	-0.6783	-0.78045
	0.883382	-0.88739	-0.87356
	-0.04889	-0.34108	-0.11039
	0.877664	-0.82152	-0.89021
avg	0.6307	0.705	0.7262
4	0.965773	-0.95534	-0.93927
	0.933604	-0.94589	-0.91971
	0.206544	-0.52426	-0.57915
	0.944945	-0.95102	-0.97175
	0.800487	-0.82739	-0.93309
	0.929325	-0.8975	-0.86914
avg	0.7968	0.8502	0.8687
5	0.999281	-0.99951	-0.98594

	0.945113	-0.92236	-0.90957
	0.747612	-0.79842	-0.93035
	0.959428	-0.9777	-0.91177
	0.736704	-0.74869	-0.68815
	-0.98	0.980852	0.963135
avg	0.8947	0.9046	0.8982
final Average	0.74246	0.78598	0.8139

7.5 Lung pressure result summary:

The goal of this experiment was to find a relation between the lung pressure and the ECG signal. Positive and negative pressures were recorded along with two channel ECG signals (refer to section 6.1). However, the negative pressure results were discarded due to the difficulty for subjects to maintain a negative pressure for the required time. Moreover, most of the subjects were not able to produce a linearly increasing negative pressure and the variation of the pressure occurred too fast for the heart rate to be analyzed.

Most of the subjects were able to produce a linear positive pressure, yet they couldn't maintain it for an extended period of time resulting in a low number of data points to compare. Typically, the pressure was maintained for 10 seconds corresponding to 12 ECG cycles. This constitutes the biggest limitation of the experiment. Another limitation arises from the fact that it would have been difficult to measure the pressure while subjects are breathing. Instead they have to hold the breath and apply pressure. To be able to have a reference for all subjects to compare results, the lung volume

had to be kept constant during the pressure measurement. To measure the effect of the lung volume we measured the lung pressure at five different volumes ranging from fully exhaled to fully inhaled volume. The volume seemed to not have a consistent influence on the correlation in most cases so it is ignored in the analysis and we average over all the results at the different volumes.

Despite the limitations we found the ECG feature that shows the best correlation with lung pressure is the R-SPeak defined as the distance between the R-point to the S-point. The correlation in general was better for the ECG2 channel from left arm to left leg. This may be due to the effect of the effort exerted by the diaphragm muscles to overcome the closure (Refer to section 6.1 for pressure experiment). The VECG area had the best correlation out of the VECG features. However, all the VECG features were characterized by very scattered patterns when plotted against the lung pressure (Refer to scatter plots Appendix 2).

The principal component analysis turned out to be not very useful in improving the R-Peaks since only very few points are available for the evaluation of the bases.

8 Elementary Result Summary:

The ECG signal can be a useful tool to measure different physiological parameters at one time. This can be done by revealing the codes hidden

within the ECG signal that carries the vital information about physiological activity other than the cardiac one. Respiration activity is one of these activities since it has a clear influence on the ECG signal by imposing a physical change on the ECG signal channel by changing lung volume and lung pressure.

The lung volume was found to have a good correlation with the ECG features such as R-peak and Pulse area. Also, the relational ECG (VECG) signal had at least one feature with reasonably good correlation per subject. In addition, PCA proved to be a very good tool that can refine the signal and increase the correlation with the lung volume. In addition, it showed a potential to indicate apnea events via changes of the dominant Eigen vector, which takes on constant values (flat patterns) during apnea events. In case of all ECG features, the ECG1 taken from the left to the right arm showed the best correlation with lung volume. This was expected since the physical channel of ECG1 spans more across the lungs than the one of ECG2.

The lung pressure was very difficult to examine experimentally especially its negative values. Therefore, only positive pressure was considered. However, even in this case it was very difficult to obtain enough data points that would allow to draw solid conclusions from the results because the experiments, which required the subjects to stop breathing while applying pressure, was very demanding to the subjects. Despite the limitations, we obtained some results that indicate a correlation between the ECG features and the lung pressure. The R-SPeak showed the highest correlation out of the features. Interestingly, in this case the best results were obtained from the ECG2, which spans from the left arm to the leg. The reason might be that upon

applying lung pressure the diaphragm muscles exert an effort, which affects the ECG2 more than the ECG1. The application of PCA does not significantly improve the results due to the lack of enough ECG pulses to have a good representation of signal in terms of PCs.

In summary, the ECG signal showed correlation with the lung volume when considering the single channel features. In addition, the VECG showed some correlation with lung volume, but the results were rather inconsistent. This is mainly caused by limitations in the experiments, and more measurements need to be carried out.

9 Enhanced Algorithms:

In an attempt to find a higher correlation of the ECG signal and the lung volume, several enhanced algorithms were derived. Since the maximum correlation of the ECG signal with the lung volume was around 71% without PCA and 74% with PCA, the correlation was still moderate, and better values seemed feasible. In addition the VECG produced inconsistent results as for some subjects the correlation was high and for others there was no correlation at all.

9.1 Filtering enhancement:

The ECG signal and lung volume were filtered with a band pass filter (BPF) to remove the DC components and noise superposed on it. Originally, the signals were first filtered from 0.05 to 150 Hz during recording and then filtered by a BPF with corner 0.2 Hz and 40 Hz. These corner frequencies were chosen since the human respiration frequency is around 0.2 Hz and the upper boundary of 40 Hz turned out to not affect the regular shape of the ECG signal while it eliminates the 50 Hz noise coming from the power grid signal (Refer to sections 6.1 and 7.1 for experiments description). In an attempt to improve the results, simulations were performed with different values of the lower corner frequency of the BPF, and it turned out that the calculated correlation changes when changing the lower corner frequency.

Figure 29 shows the correlation of the R-Peak and lung volume as a function of the lower corner frequency

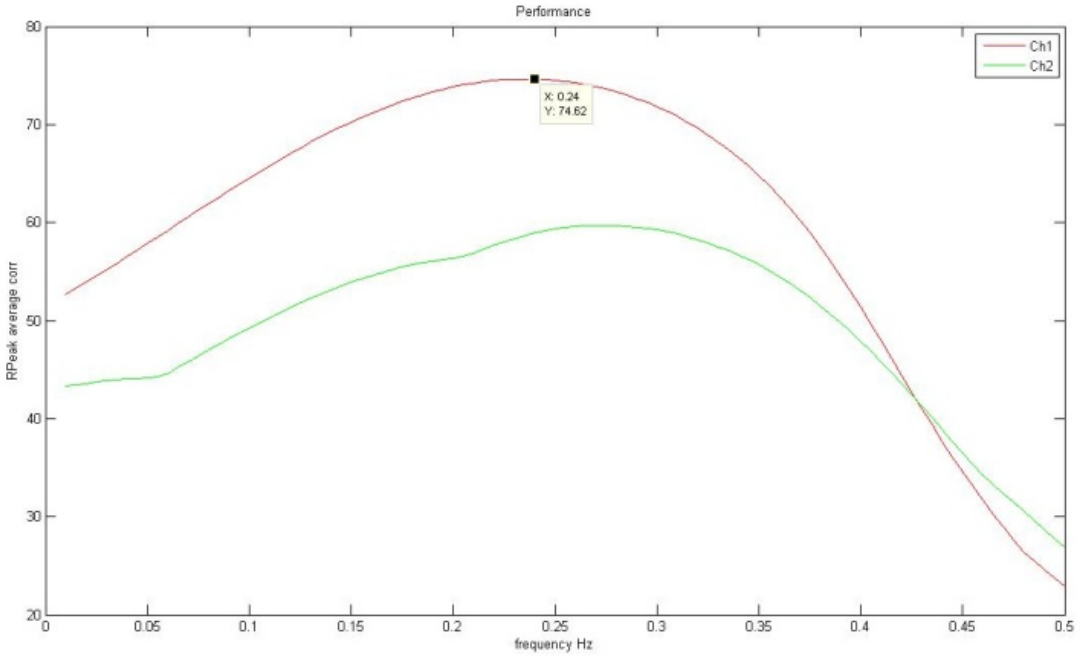

Figure 29: performance sensitivity to changes of the lower corner frequency of the band pass filter for ECG1 and ECG2

As can be seen, the highest correlation can be obtained with a BPF with corner frequencies of 0.24 Hz and 40 Hz. With these filter parameters, correlation increased from 71% to 75%.

Table 15 includes the correlation results of ECG Peak features with lung volume after applying the optimized filter band (Refer to Section 6.2.1 and Appendix 1 for features description).

Table 19: correlation of the various Peak features vs. lung volume with optimized corner frequencies [0.24-40 Hz]

Subj	R-Peak1	R-Peak2	Q-R Peak1	Q-R Peak2	R-S Peak1	R-S Peak2
1	79%	77%	72%	80%	71%	79%
2	91%	74%	89%	65%	92%	75%
3	86%	70%	88%	81%	87%	80%
4	67%	9%	72%	38%	78%	40%
5	91%	50%	92%	59%	92%	28%
6	23%	64%	2%	64%	30%	59%
7	83%	67%	88%	75%	87%	85%
8	76%	61%	80%	27%	81%	16%
avg	75%	59%	73%	61%	77%	58%

Unlike the elementary algorithm (Section 6.2.1) the Q and S points where extracted according to enhanced algorithms that are explained in the following section 9.2.

Overall, the highest correlation was obtained with R-SPeak1 of ECG1 with a value of 77% and with the smallest error factor of 0.72%.

Table 20: scattering error of the Peak features vs. lung volume when optimized filter [0.24-40Hz] is applied.

Subj	R-Peak1	R-Peak2	Q-R Peak1	Q-R Peak2	R-S Peak1	R-S Peak2
1	0.52	0.56	0.59	0.53	0.57	0.60
2	0.90	0.92	0.99	0.88	0.72	0.89
3	0.56	0.94	0.50	1.00	0.42	0.77
4	0.65	0.33	0.63	0.41	0.45	0.38
5	0.95	0.74	0.85	0.66	0.78	0.88
6	1.07	0.75	1.26	0.72	1.17	0.82
7	1.05	0.89	0.96	0.89	0.96	0.74
8	0.83	1.79	0.76	2.69	0.68	3.09
avg	0.82	0.87	0.82	0.97	0.72	1.02

9.2 Enhanced Algorithms for Q-S detection:

The elementary algorithm for indicating Q and S points as defined in section 6.2.1 was updated in an attempt to improve its efficiency. Unlike the elementary algorithm, which extracts the 2 minimums of the ECG pulse that correspond to the Q and S points, the new algorithm treats the area before and after the R point separately and searches for Q and S points independently. Since the length of the QRS complex is 100 ms and the R-peak is approximately in the middle of this time window [2], the Q and S points

can be obtained by applying a window of 50 ms before and after the R-peak and finding the major minima within this sections (figure 30).

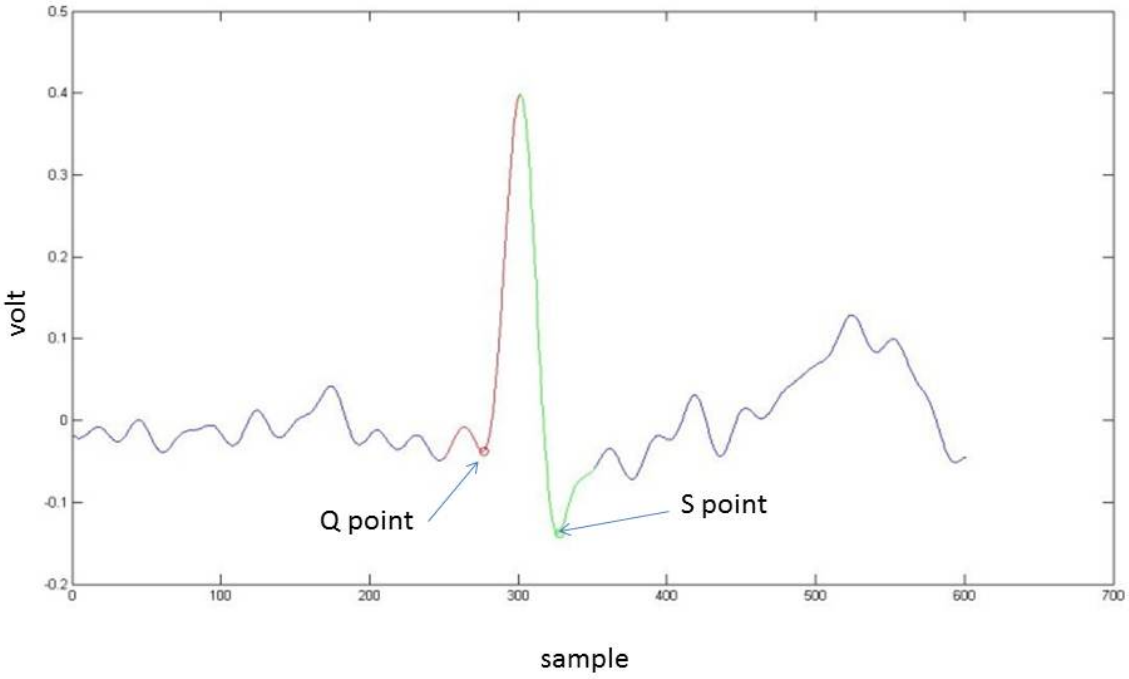

Figure 30: Windows applied to the ECG signal for enhanced Q and S point detection

The new algorithm is an improvement to the original one in the sense that when focusing on the Q and S points separately the problem of falsely finding two minimums on one side of the R-Peak is remedied.

In some cases, the minima couldn't be extracted because the Q or S points were not significant enough. In such a case, a different algorithm was applied that utilizes the minimum absolute slope around the R point. Such a case is shown in figure 31, where an insignificant Q point can be observed that had been extracted by finding the minimum absolute slope.

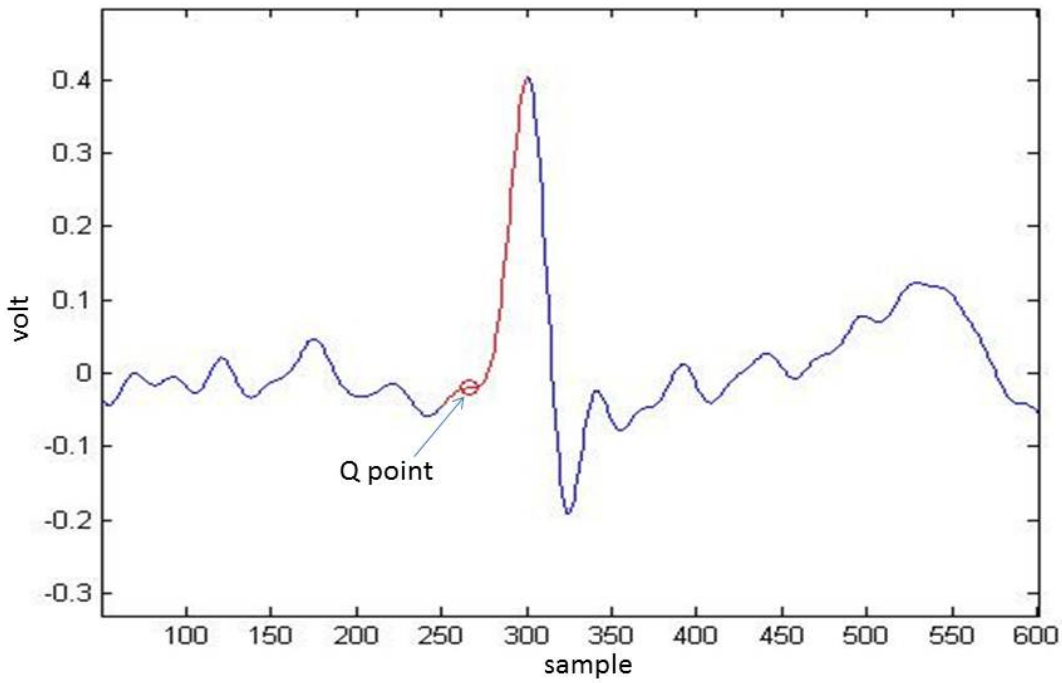

Figure 31: detection of insignificant Q points

The precision in extracting the Q and S points had an impact on the calculated correlation results. Applying the enhanced algorithms to find the points, the correlation was increased from 69% to 77% (table 19) for the R-SPeak and from 59% to 75% for the Q-SArea. The following tables (21 and 22) show the correlation of ECG area features and lung volume.

Table 21: correlation of areas vs volume with enhanced algorithm for Q and S point extraction and optimized filter [0.24-40Hz]

Subj	PulseArea1	PulseArea2	Q-S area1	Q-S area2
1	59%	76%	77%	81%
2	90%	43%	90%	85%
3	42%	59%	81%	78%
4	59%	44%	75%	51%
5	77%	34%	89%	42%
6	33%	48%	25%	30%
7	47%	57%	83%	75%
8	67%	30%	83%	9%
avg	59%	49%	75%	56%

Table 22: scattering errors of areas vs lung volume

Subj	PulseArea1	PulseArea2	Q-S area1	Q-S area2
1	0.40	0.58	0.52	0.53
2	0.65	1.01	0.92	0.89
3	0.66	1.11	0.48	1.03
4	0.53	0.78	0.49	0.37
5	0.95	0.82	1.05	0.78
6	0.49	0.80	0.81	0.76
7	1.72	1.07	1.01	0.88
8	0.73	1.20	0.72	1.77
avg	0.77	0.92	0.75	0.88

In addition to the enhancement of algorithms described before, some of the original definitions of features (section 6.2.1) were changed depending on the elementary results.

PulseArea and Q-SArea were kept as in section 6.2.1 as shown in the following figures:

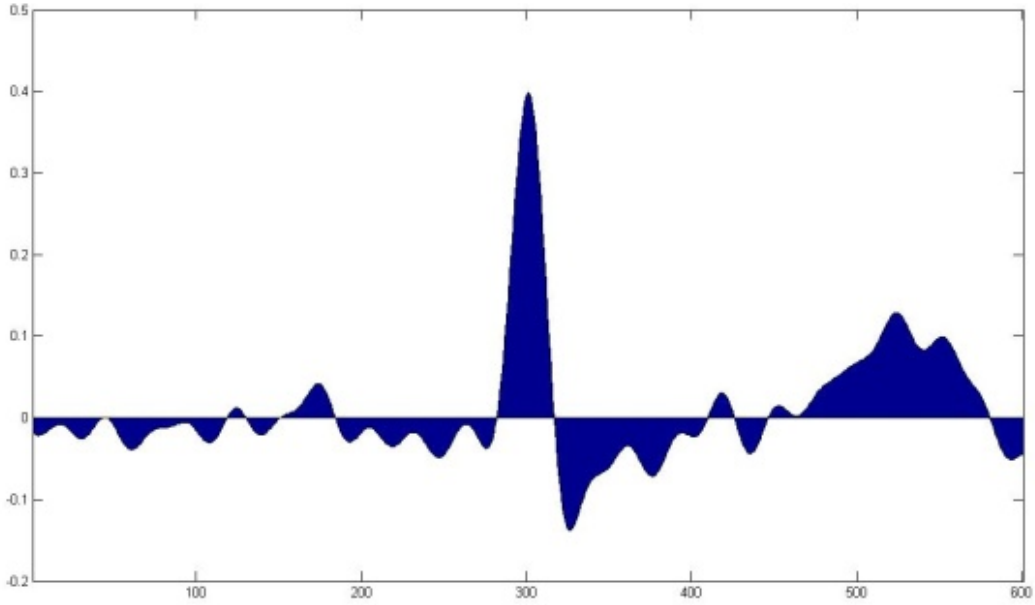

Figure 32: Pulse area

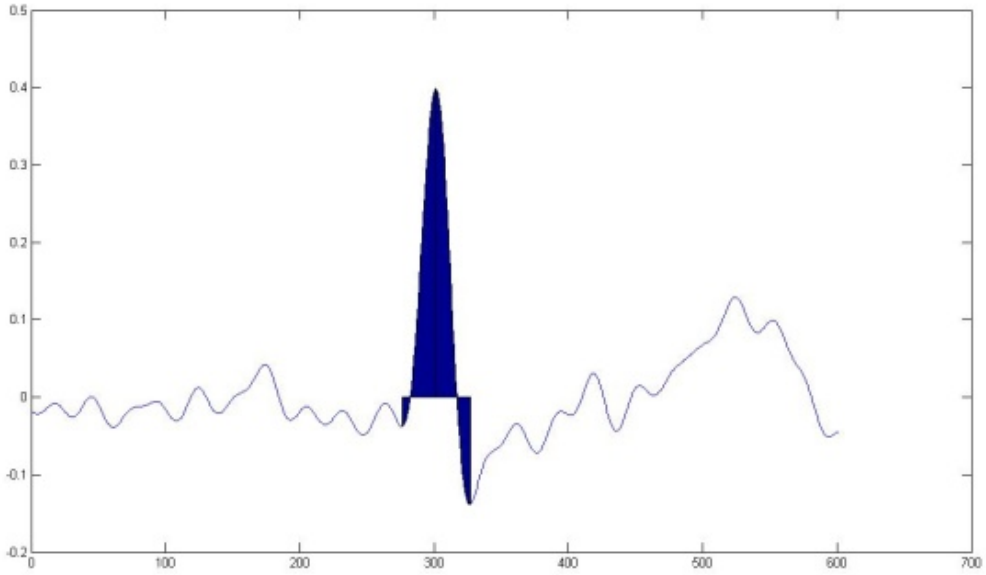

Figure 33: Area from Q-S points

On the other hand, a new definition of the Q-RArea and R-SArea is developed to focus more on the Q to S period. The new Q-RArea is the area that extends

from the Q to the R point and the R-SArea is the area from the R to the S point as shown in Fig 34 and 35.

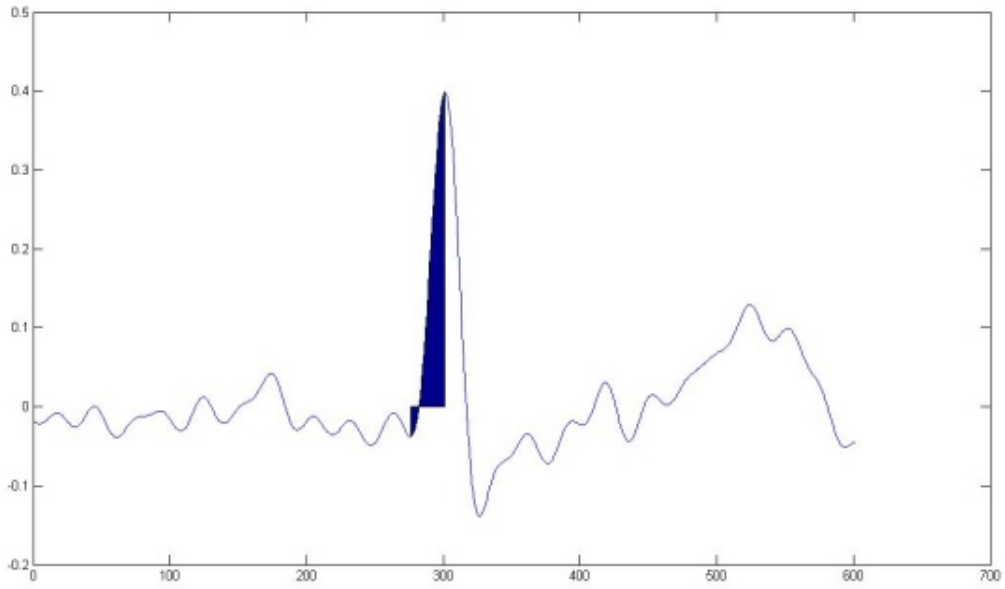

Figure 34: QRS front area Q-RArea

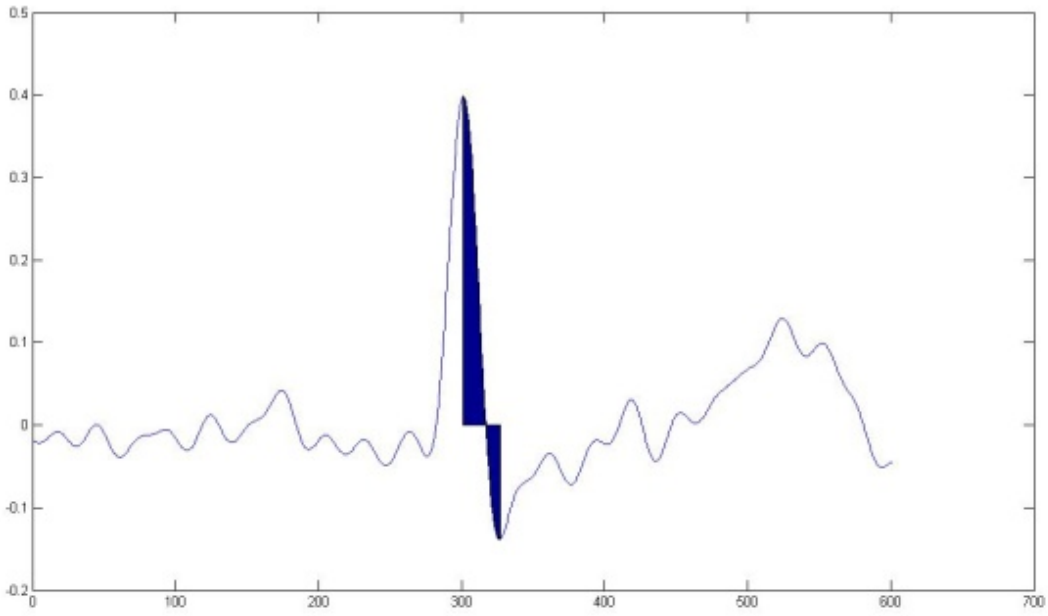

Figure 35: QRS end area R-SArea

The results summarized in table 23 shows that the Q-RArea and R-SArea correlate with the lung volume. However, the Q-RArea has a higher

correlation with 72% than the R-SArea with 61%. On the other hand, the RatioArea of the Q-RArea to R-SArea has very poor correlation with lung volume because the both features have relatively similar correlation and in the same direction so the ratio removes the correlation information embedded in the two areas. Table 23 and 24 include the Q-RArea, R-SArea and RatioArea correlation with lung volume and their scattering error.

Table 23: correlation of Q-RArea, R-SArea and RatioArea Vs. lung volume.

Subj	Q-RArea1	Q-RArea2	R-SArea1	R-SArea2	RatioArea1	RatioArea2
1	69%	80%	74%	78%	1%	9%
2	89%	88%	89%	79%	62%	53%
3	86%	80%	60%	73%	78%	56%
4	60%	54%	65%	21%	12%	29%
5	88%	52%	87%	27%	1%	25%
6	19%	40%	17%	14%	3%	10%
7	83%	67%	83%	78%	10%	18%
8	84%	28%	77%	15%	46%	47%
avg	72%	61%	69%	48%	27%	31%

Table 24: scattering error of of Q-RArea, R-SArea and RatioArea vs. lung volum.

Subj	Q-RArea1	Q-RArea2	R-SArea1	R-SArea2	RatioArea1	RatioArea2
1	0.62	0.53	0.58	0.58	0.63	0.44
2	1.13	0.93	0.87	1.00	0.98	0.86
3	0.63	1.08	0.49	1.04	0.59	0.64
4	0.76	0.49	0.56	0.50	0.91	0.64
5	1.08	0.75	1.09	0.93	0.88	0.69
6	0.80	0.73	0.96	1.20	0.87	1.40
7	1.05	0.97	1.01	0.86	0.71	0.68
8	0.77	1.86	0.74	2.89	0.63	3.08
avg	0.85	0.92	0.79	1.13	0.77	1.05

9.3 Enhancement of VECG features' Algorithm:

Previously VECG features such as elongation, angle and area were extracted according to the methods explained in section 7.1.3. Due to the complexity of the VECG plot the algorithm failed to extract accurate values for the features in some cases. The original algorithm defined the VECG Elongation found the distance from the origin to the location of the curve that was furthest away from the origin. An observation of the previous definition is that this instance coincides with the R-Peak of ECG1 in most cases. Therefore, a new definition of the VECG Elongation to be the instant at the ECG1 R-Peak was implemented.

The original algorithms' major flaw was normalizing the VECG plot. The normalization point was defined as the zero point. This definition lacks accuracy because it is not the common point for all ECG pulses of the subjects in all cases.

An improved definition uses the point that most of the beats pass through. Consequently, the definition of the zero point was updated to be the point that has the highest density of points on the VECG plot. An algorithm that divides the VECG plot into squares and counts the number of points in each square was developed to indicate the densities of all positions of the VECG plot. Figure 36 visualizes the density of the points of the VECG that indicates the normalization point shown in Figure 37.

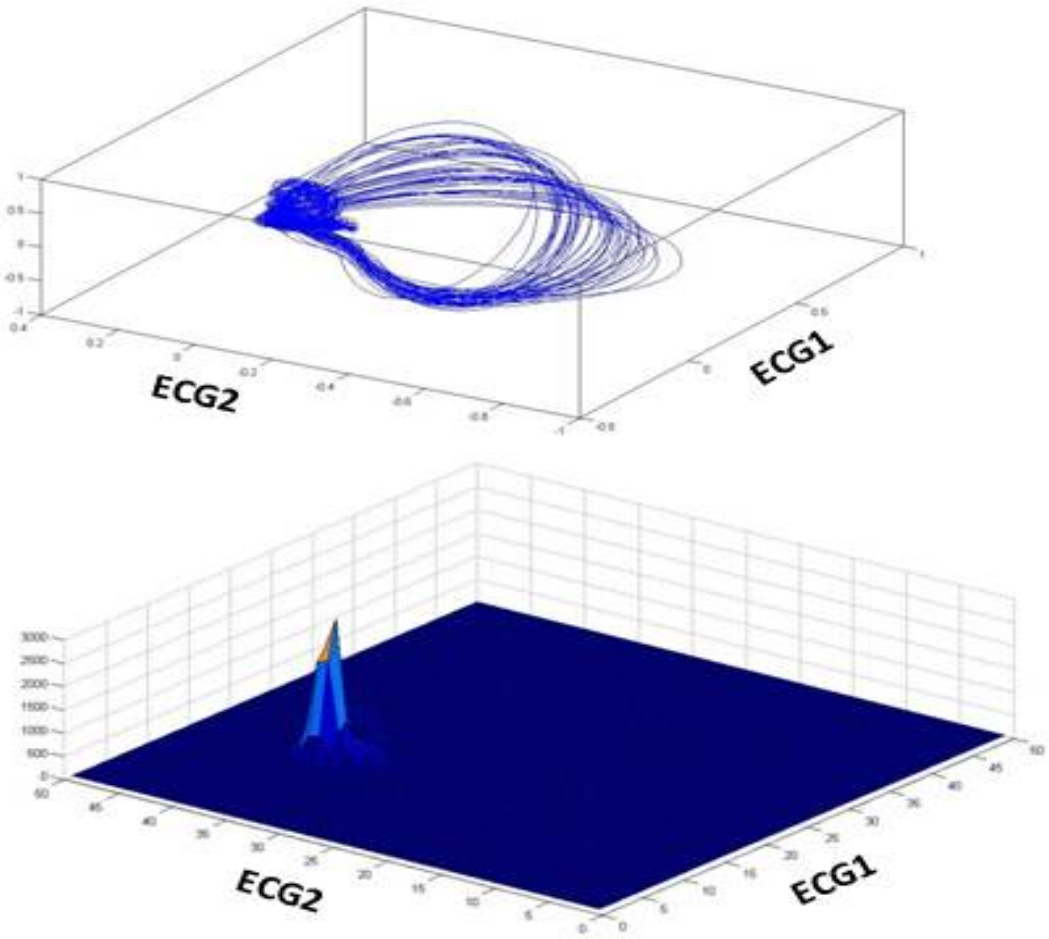

Figure 36 : Point Density Distribution of the VECG.

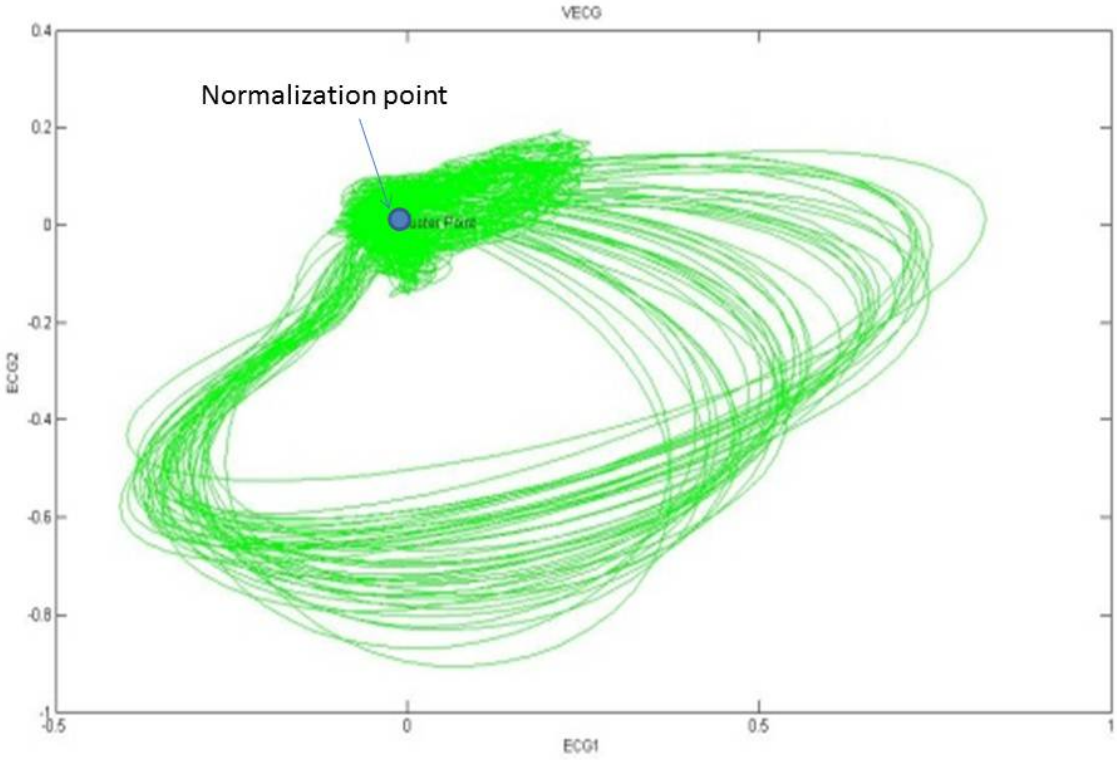

Figure 37: Normalization point

The VECG features elongation and angle are then calculated with reference to this point as shown in the following figure.

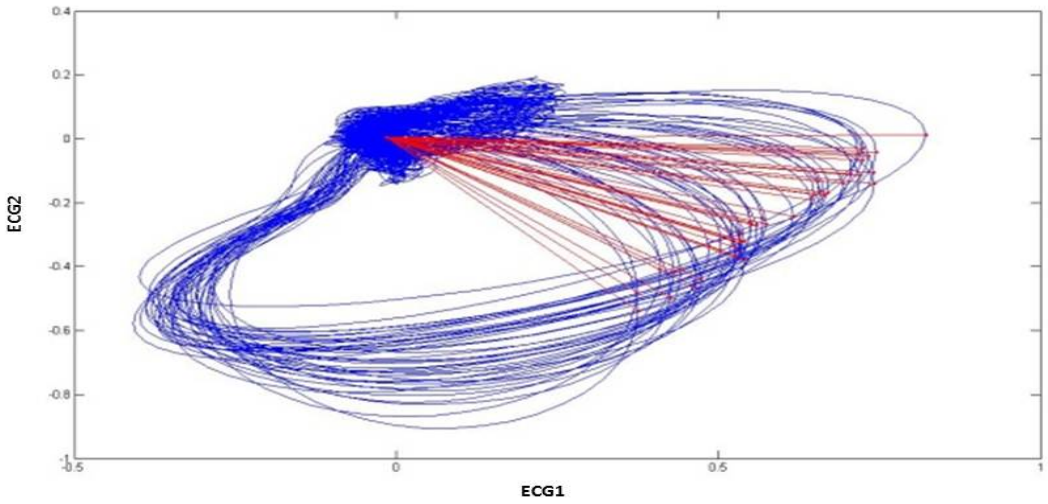

Figure 38: VECG Elongation line

For all VECG features the correlation with the lung volume have been enhanced individually especially the VECG inclination angle correlation enhanced to reach around 61% compared to 42% in section 7.1.3. Also, the maximum value of each of the features enhanced to reach up to 79% as compared to 70% in section 7.1.3. Table 25 and 26 summarize the correlation and scattering error of VECG features after applying the normalization technique.

Table 25: correlation of VECG features extracted using improved definitions vs. lung volume

Subj	Elongation	Angle	Area	max
1	61%	80%	9%	80
2	81%	90%	89%	90
3	85%	78%	51%	85
4	6%	59%	64%	64
5	34%	90%	51%	90
6	36%	7%	77%	77
7	10%	70%	43%	70
8	78%	18%	84%	78
avg	49%	61%	59%	79%

Table 26: Scattering Error of VECG features

Subj	Elongation	Angle	Area	Error of Max
1	0.32	0.50	1.71	0.50
2	0.60	1.84	0.48	1.84
3	0.29	1.35	0.71	0.29
4	0.62	0.43	0.77	0.77
5	0.53	0.31	2.38	0.31
6	0.95	1.44	0.94	0.94
7	1.13	1.26	1.43	1.26
8	0.78	3.55	2.37	0.78
avg	0.65	1.34	1.35	0.84

9.4 Enhancement of PCA signals reconstruction:

9.4.1 PCA Single channel features:

The correlation of PCA filtered ECG signal features also benefitted from selecting the optimum BPF [0.24-40 Hz]. The correlation increased from 74% to 77%. However, it didn't exceed the value found for the normal features, which was also 77% in case of the R-SPeak. Therefore, unlike the elementary approach of constructing ECG features using the dominant PC, the performance when using several PCs was investigated. Figure 39 shows the result of the simulation by varying PCs from 1 to 30.

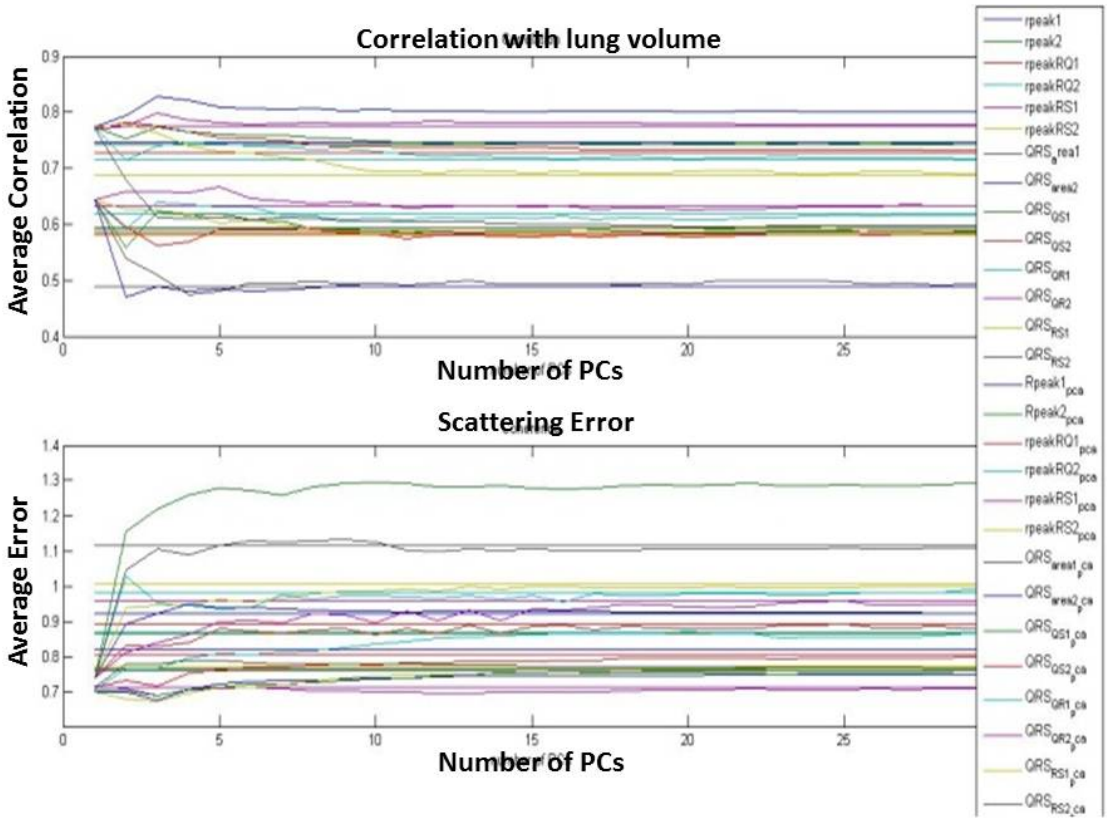

Figure 39: ECG features performance when using several PCs

From figure 39 it can be seen that R-Peak1 reconstructed by applying PCA turns out to have the highest correlation with lung volume compared to all the other reconstructed features. Further, the R-SPeak1 has the best correlation with the original features without performing PCA. Figure 40 shows the performance of both.

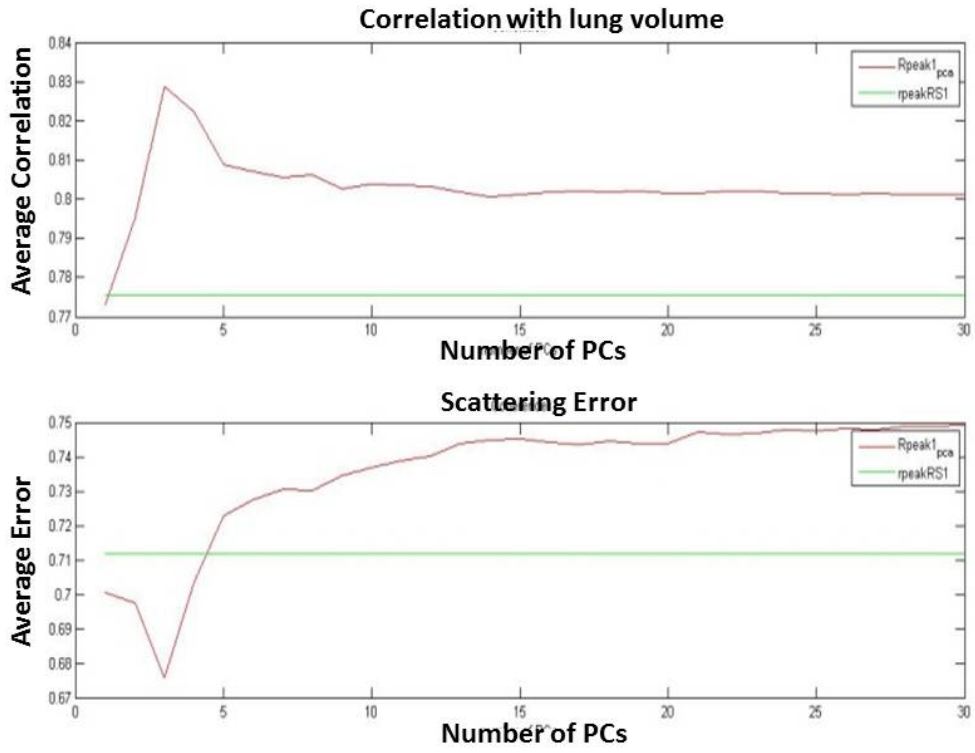

Figure 40: Best PCA reconstructed feature and Best original feature performance

Note that the R-SPeak1 original features appear as a straight line as it doesn't benefit from adding more PCs. Figure 40 shows the optimum case is using 3 PCs to reconstruct ECG features providing a maximum correlation of 82 %. This is an increase of 6% compared to the R-SPeak1 without applying PCA and 5% compared to the results obtained with 1PC.

The PCA decomposes the signal into its orthogonal components (PCs). Some of these bases are affected more by the lung volume than others that are considered as noise in this case. Therefore, when increasing the number of PCs used to reconstruct the signal the correlation for some features increases. The number of PCs reaches an optimum value before it decreases when the sub-procedures that are considered as noise are used to reconstruct the signal. The figures 41 to 43 show the relation between the

average value of the correlation for single channel features relative to the reconstructed features using 1,2 and 3 PCs.

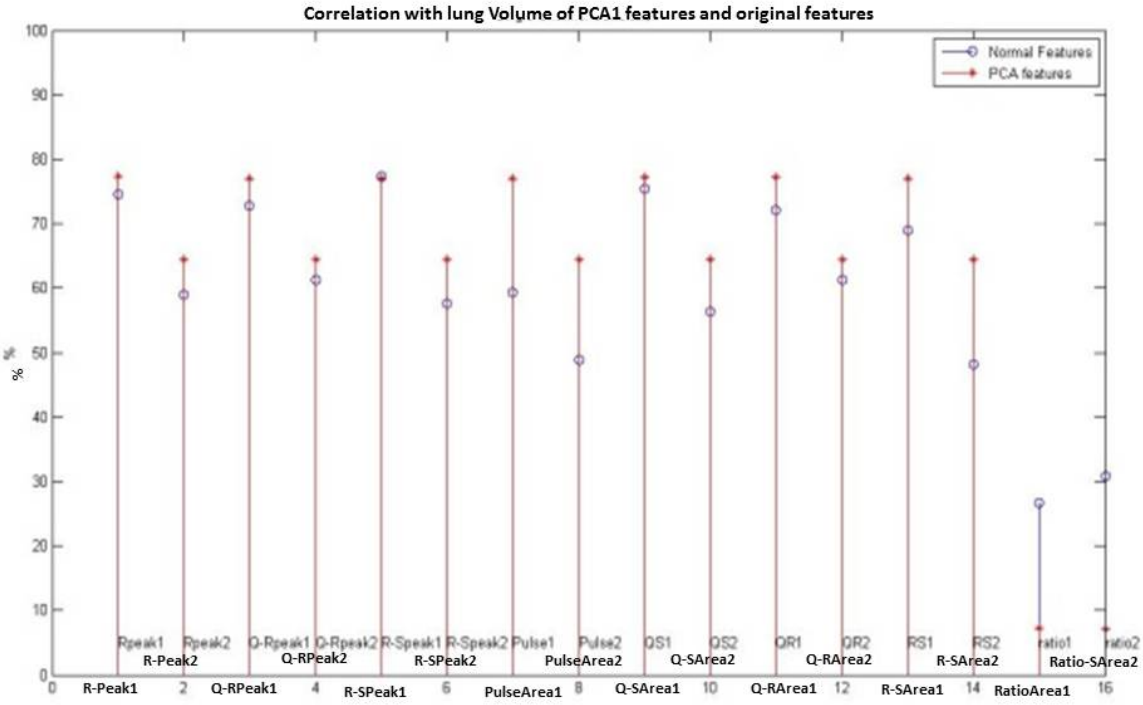

Figure 41: correlation using 1 PC

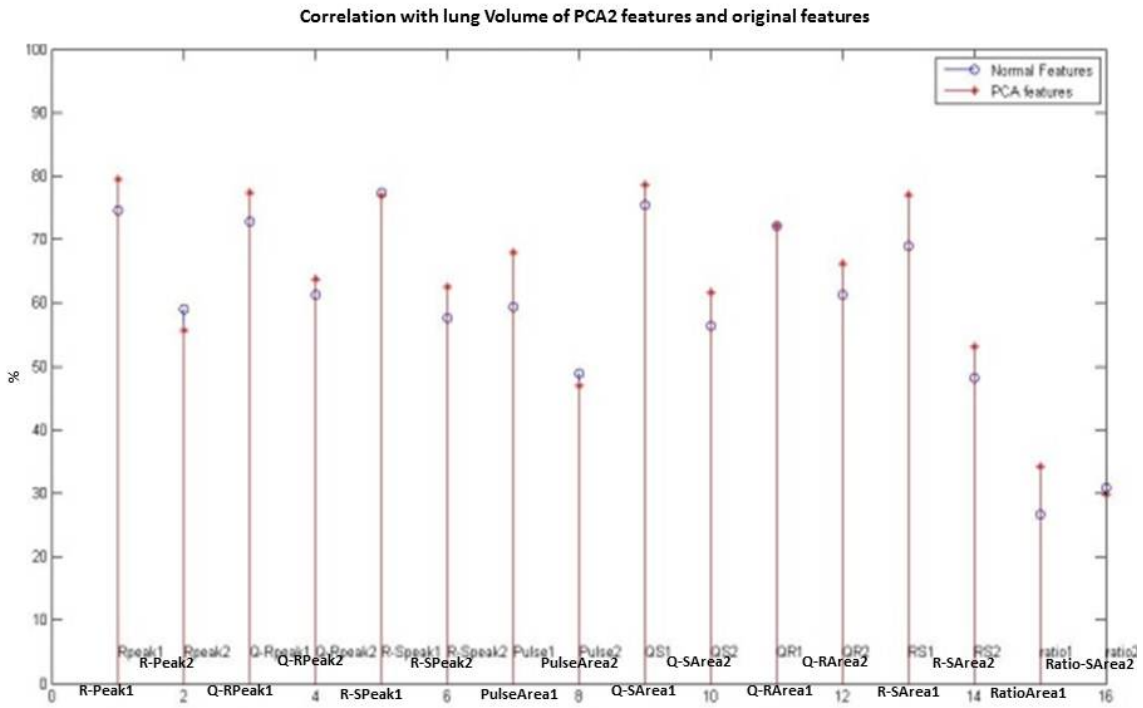

Figure 42: correlation using 2 PCs

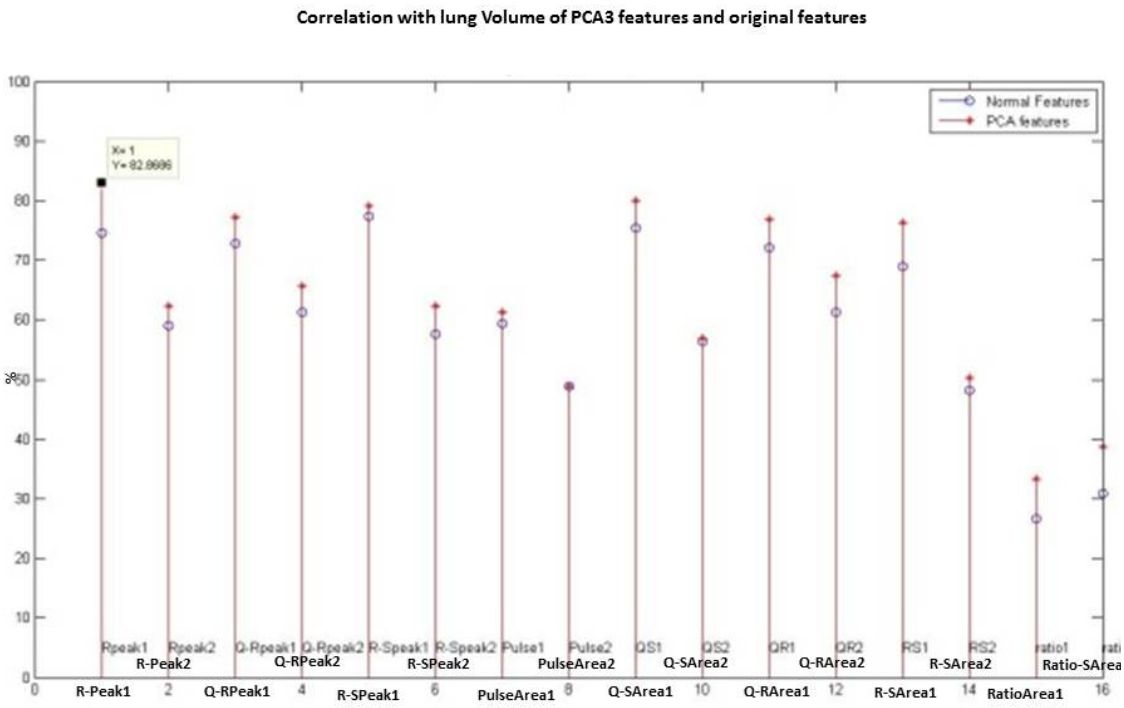

Figure 43: correlation using 3 PCs

As figure 31 shows the correlation values are nearly the same for a certain channel for most of the features using only one PC because there is only one degree of freedom. As more degrees of freedom are added by adding more PCs (figure 42 and 43) the correlation values start varying reaching the highest value of 83% for the R-Peak and with the least scattering error compared to the original features. Table 27 and 28 show the correlation of single channel features using PCA3 (reconstructed using 3 PCs) and their corresponding scattering errors, respectively:

Table 27: correlation of PCA peak features using 3 PCs vs. lung volume

PCA (3PCs)						
Subj	R-Peak1	R-Peak2	Q-R Peak1	Q-R Peak2	R-S Peak1	R-S Peak2
1	80%	78%	77%	80%	77%	81%
2	91%	59%	91%	72%	92%	79%
3	89%	51%	90%	82%	89%	83%
4	74%	39%	80%	49%	82%	45%
5	90%	62%	92%	58%	92%	45%
6	72%	48%	16%	67%	31%	64%
7	83%	76%	88%	83%	88%	83%
8	83%	85%	83%	34%	81%	18%
avg	83%	62%	77%	66%	79%	62%

Table 28: Scattering Error of PCA peak features using 3 PCs vs. lung volume

PCA (3PCs)						
R-Peak1	R-Peak2	Q-R Peak1	Q-R Peak2	R-S Peak1	R-S Peak2	R-Peak1
0.45	0.69	0.48	0.54	0.46	0.55	0.45
0.86	1.77	0.89	0.80	0.74	0.77	0.86
0.48	1.21	0.43	1.02	0.41	0.70	0.48
0.38	1.36	0.39	0.28	0.37	0.28	0.38
0.99	0.72	0.87	0.69	0.81	0.82	0.99

0.56	1.18	1.28	0.71	1.32	0.68	0.56
1.02	1.01	0.98	0.74	0.98	0.73	1.02
0.67	1.81	0.68	2.28	0.68	3.10	0.67
0.68	1.22	0.75	0.88	0.72	0.95	0.68

The Q-SArea constructed by applying PCA showed a good correlation with lung volume that reached up to 80% and exceeded the value obtained with the whole pulse area as shown in the following tables:

Table 29: correlation of PCA area features using 3 PCs vs. lung volume

Subj	PulseArea1	PulseArea2	Q-SArea1	Q-SArea2
1	71%	78%	75%	79%
2	91%	38%	91%	85%
3	35%	61%	89%	74%
4	67%	40%	80%	32%
5	80%	23%	90%	50%
6	28%	52%	45%	38%
7	51%	56%	84%	80%
8	67%	43%	85%	18%
avg	61%	49%	80%	57%

Table 30: Scattering Error of PCA area features using 3 PCs vs. lung volume

Subj	PulseArea1	PulseArea2	Q-S area1	Q-S area2
1	0.45	0.57	0.52	0.54
2	0.63	0.97	0.85	0.89
3	0.63	1.11	0.41	1.09
4	0.61	0.83	0.36	0.30
5	0.96	0.76	1.00	0.78
6	0.50	0.90	0.62	0.73
7	1.71	1.12	1.01	0.76
8	0.73	1.11	0.67	1.81
avg	0.78	0.92	0.68	0.86

In case when PCA was used to reconstruct signal features the Q-RArea had a very good correlation of 77% and R-SArea showed a similar correlation (see table 31 and 32). On the other hand the RatioArea of the two areas turns out to be uncorrelated with the lung volume as noted before because of the relatively similar correlation of both areas.

Table 31: correlation of PCA partial area features using 3 PCs vs. lung volume

Subj	Q-R area1	Q-R area2	R-S area1	R-S area2	RatioArea1	RatioArea2
1	67%	79%	81%	78%	13%	8%
2	91%	89%	92%	79%	79%	72%
3	89%	75%	84%	72%	53%	61%
4	62%	46%	72%	13%	14%	33%
5	90%	58%	90%	41%	6%	32%
6	45%	61%	25%	12%	6%	25%
7	84%	75%	83%	82%	13%	24%
8	87%	56%	82%	24%	81%	54%
avg	77%	67%	76%	50%	33%	39%

Table 32: Scattering error of PCA partial area features using 3 PCs vs. lung volume

Subj	Q-R area1	Q-R area2	R-S area1	R-S area2	RatioArea1	RatioARea2
1	0.61	0.54	0.48	0.55	0.43	0.07
2	0.96	0.89	0.77	0.96	0.51	0.61
3	0.46	1.11	0.42	1.08	0.44	0.28
4	0.49	0.29	0.48	0.35	0.71	0.26
5	1.01	0.71	0.99	0.86	0.23	0.33
6	0.63	0.66	0.87	1.16	0.85	1.37
7	1.01	0.78	1.02	0.76	0.12	0.39
8	0.69	1.72	0.67	3.16	0.24	2.68

avg	0.73	0.84	0.71	1.11	0.44	0.75

9.4.2 PCA VECG features:

Due to the efficiency of the PCA in removing the irrelevant basis with respect to the lung volume, it is also applied to the VECG. The PCA algorithm is implemented on the matrix X (Refer to equation 4) that constitutes of ECG pulses of ECG1. A second matrix Y is chosen according to time instances of matrix X from ECG2 and the PCA algorithm is applied to it. The two matrices X and Y are then reshaped back to one vector in time by putting each column of X and Y after each other to be able to use the VECG features extraction Algorithms that normalize the VECG plot and fetch the corresponding features (Refer to Section 9.3). Figure 44 shows the VECG with PCA and without PCA applied.

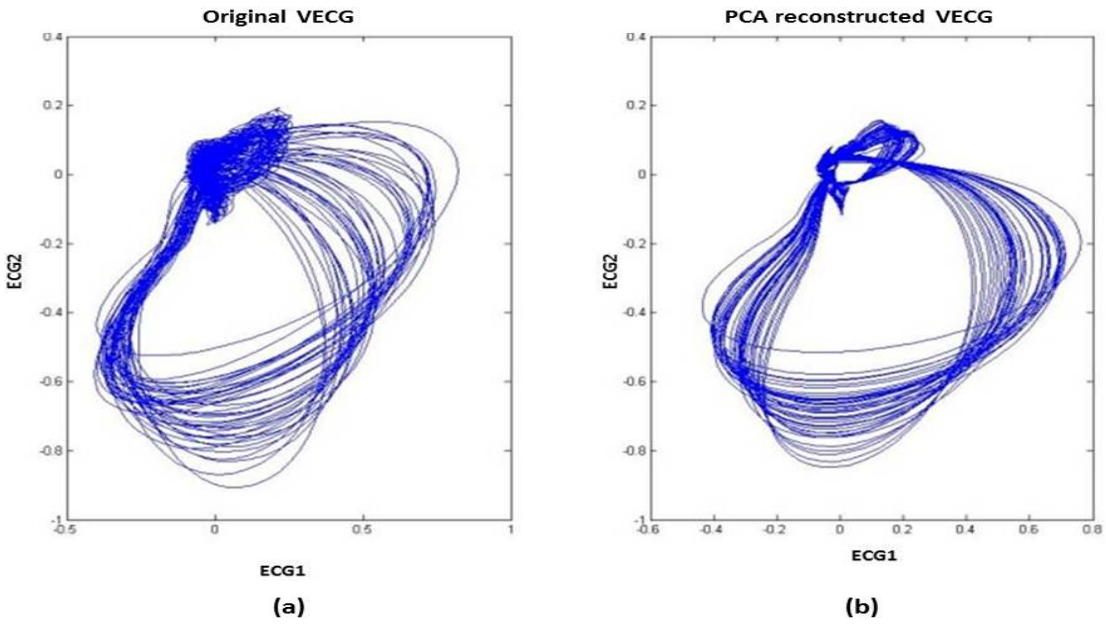

Figure 44: Comparison between the original VECG plot and Reconstructed VECG plot using PCA.

Note that the VECG constructed by applying the PCS (figure 44 b) appears smoother and with less noise.

The performances of the VECG features are studied as a function of the numbers of PCs. Figures 45 and 46 show the correlation and scattering variation with respect to the number of PCs used in the construction:

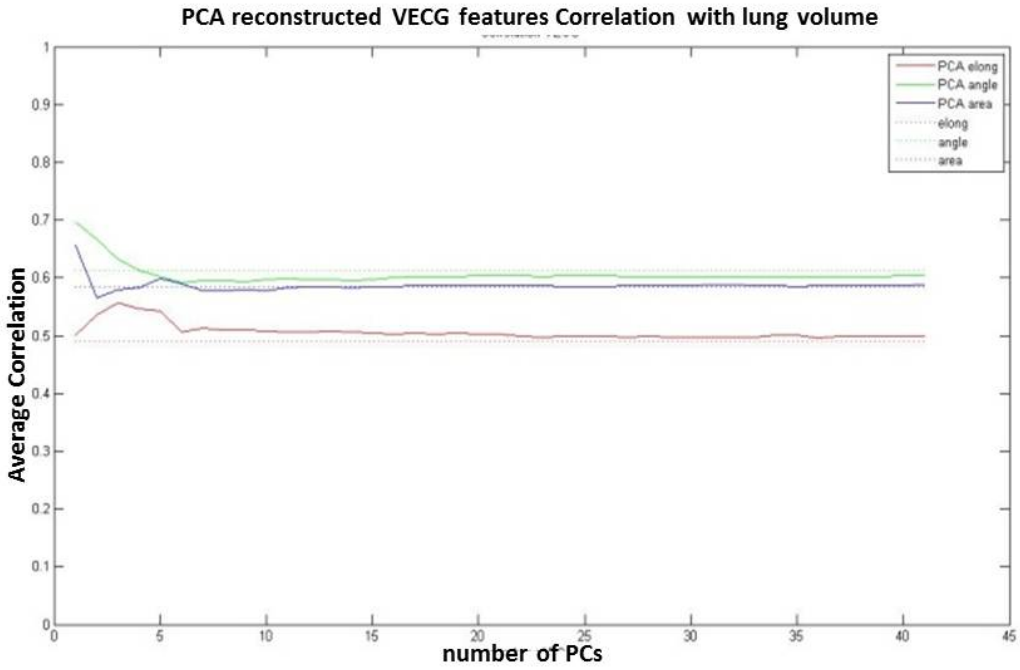

Figure 45: correlation performance of VECG as a function of the number of principal components used for the reconstruction of the signal

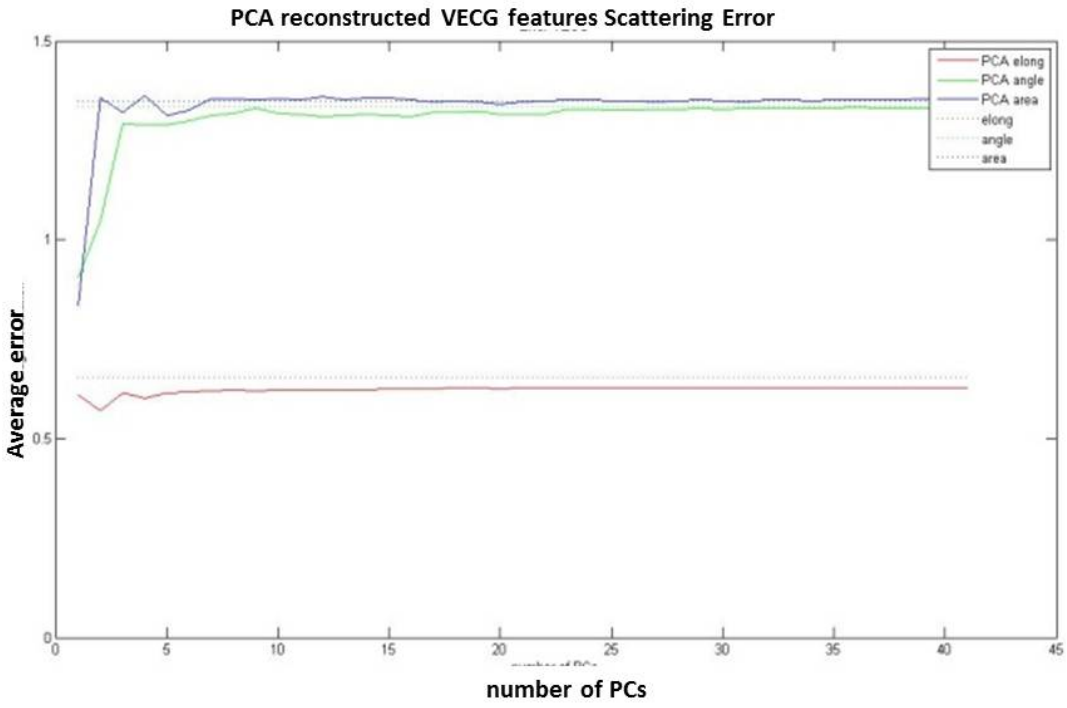

Figure 46: Error performance of VECG as a function of the number of principal components used for the reconstruction of the signal

Figure 45 shows an interesting phenomenon that not all the features change in the same direction. VECG Area and Angle provide the best results using only 1 PC while the elongation of the VECG provides the best results when using 3 PCs. VECG angle has a monotonically decreasing performance with increasing number of PCs. The performance of the VECG area first decreases, then increases and finally decreases again. Similarly, the performance of the VECG elongation increases and then decreases. The performances of the three features are closest using 3 PCs but then they diverge.

The VECG features which provided the best results so far had a better correlation when applying the PCA than without PCA. For example, VECG Elongation with 3 PCs, area and angle at 1 PC. Table 33 and 34 show the

results of correlation and scattering, respectively, of each feature when using the optimum number of PCs for the reconstruction of the VECG feature.

Table 33: correlation of PCA VECG features vs. lung volume when using the optimum number of PCs for the reconstruction

	3 PC	1 PC	1 PC	
Subj	**Elongation**	**Angle**	**Area**	**Max**
1	68%	80%	40%	80%
2	82%	87%	83%	87%
3	86%	87%	50%	87%
4	16%	74%	76%	76%
5	41%	87%	88%	88%
6	47%	10%	60%	60%
7	21%	72%	60%	72%
8	84%	60%	69%	84%
avg	56%	70%	66%	79%

Table 34: scattering error of PCA VECG features vs. lung volume when using the optimum number of PCs for the reconstruction

	3 PCs	1 PC	1 PC	
Subj	**Elongation**	**Angle**	**Area**	**Max**
1	0.31	0.48	0.39	0.48
2	0.56	1.07	0.55	1.07
3	0.29	0.70	0.68	0.70
4	0.62	0.22	0.31	0.31
5	0.53	0.30	0.79	0.79
6	0.98	1.11	1.30	0.98
7	0.99	1.24	1.28	1.24
8	0.62	2.13	1.38	0.62
avg	0.61	0.91	0.83	0.77

Each feature had on average a better correlation than the original case discussed in section 7.1.3 with the best correlation obtained by the VECG angle. Application of the PCA increased the correlation of the VECG elongation from 49% to 56% corresponding to an increase of 14%, and the correlation of the angle from 61% to 70% corresponding to an increase of 15%. It also, raises the correlation of the area from 59% to 66% corresponding to an increase of 12%.

10 Enhanced Algorithms Summary:

Due to moderate correlation results of the elementary algorithms, the new enhanced methods, described in section 9, are devised to have more effective algorithms for features extraction and procedures for signal refinements. The correlation of the ECG signals showed sensitivity to the corner frequencies of the BPF filter, which limits the signal bandwidth to 0.24-40 Hz thus eliminating interference sources like near DC components and 50 Hz power supply coupling. The bandwidth from 0.24-40 Hz turned out to be the optimum and retained most of the respiration entropy embedded in the ECG signal.

Enhanced features fetching algorithms also increased the correlation values by accurately indicating Q and S points of ECG pulses hence providing more accurate feature measurements. In addition, the normalization of the VECG to the point of highest density yields more accurate VECG features.

The PCA refinement technique isolated the sub-procedures that are not related to the lung volume. It was used as a way to tune the ECG signals to the PCs that contain the respiration information. This technique provided the best correlation results in both independent channel features and VECG channel features.

By applying the enhanced techniques, the correlation of the ECG features with lung volume increased with the best value provided by the R-S peak with 77%. It also enhanced most of the area features especially the Q-S area, which reached up to 75%. On the other hand the RatioArea seemed to be uncorrelated with the lung volume, which shows that the front and end area change together in the same direction with lung volume changes and this

information is canceled in the ratio of the two. Applying the PCA, the best correlation in this experiment of 83% was obtained by using 3 PCs. In case of the VECG not all features showed the best correlation with a certain number of PCs. For instance the VECG area and angle showed highest correlation when using 1 PC but the elongation turned out to correlate the most when using 3 PCs.

The enhancement techniques used showed an impact on the correlation and the error and provide potential to be used for correlations of other phenomena such as lung pressure and ECG signal.

Appendix 2 (scattering Plots)

Lung Volume Scattering Plots:

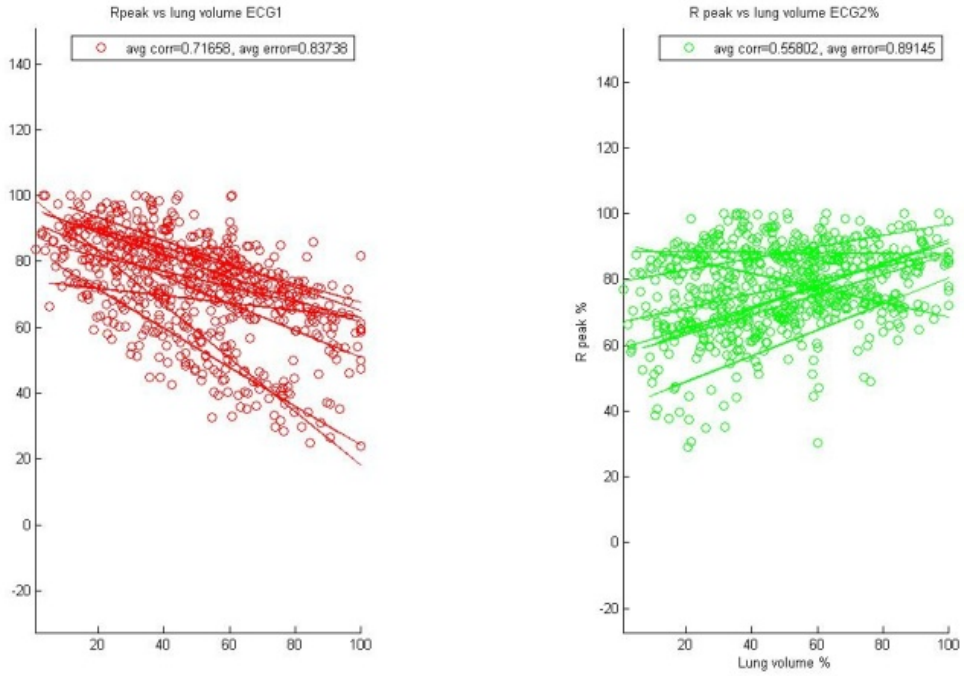

Figure 47: R-Peak Correlation with lung Volume

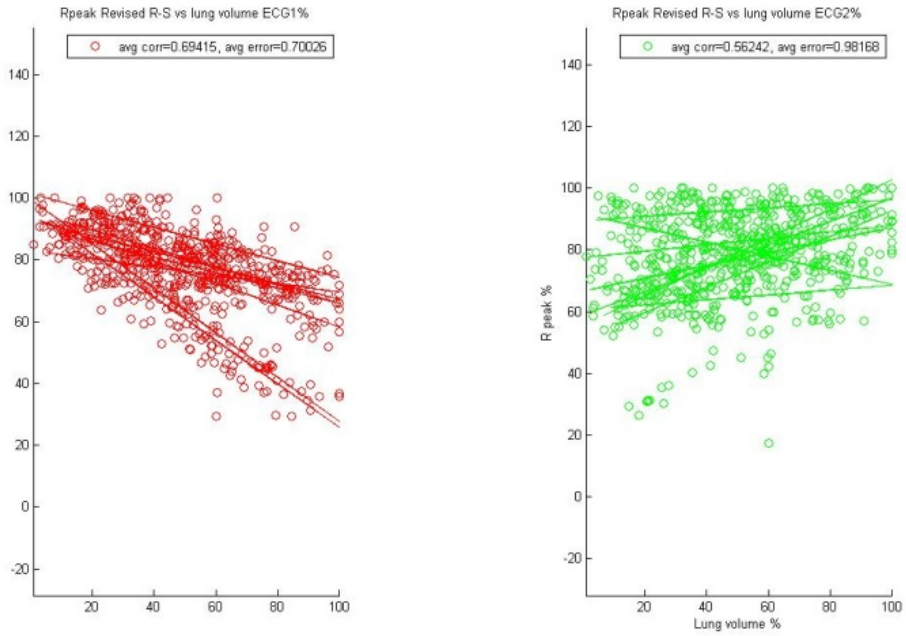

Figure 48: R-SPeak from R to S point correlation with lung volume

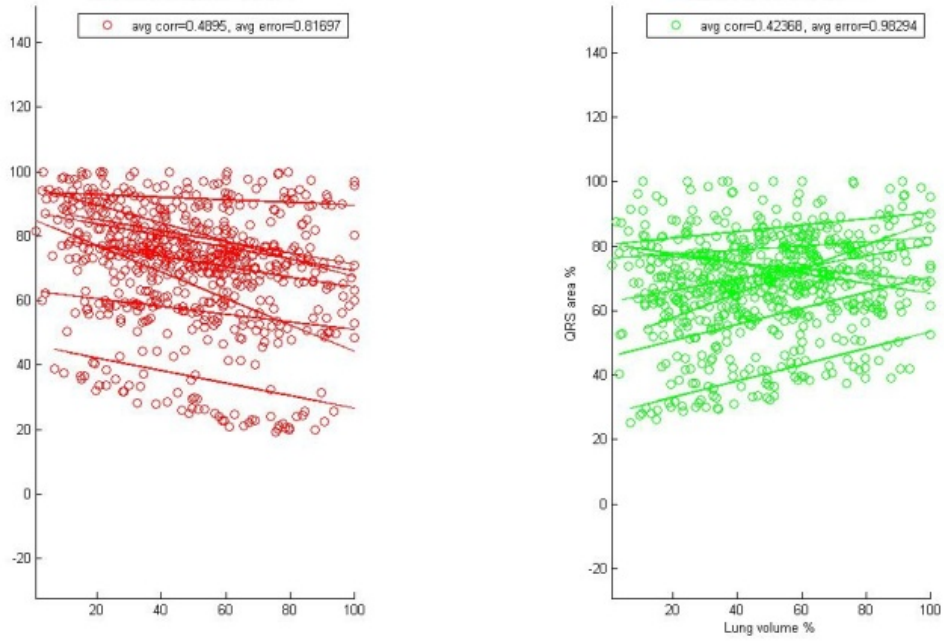

Figure 49: PulseArea correlation with lung volume

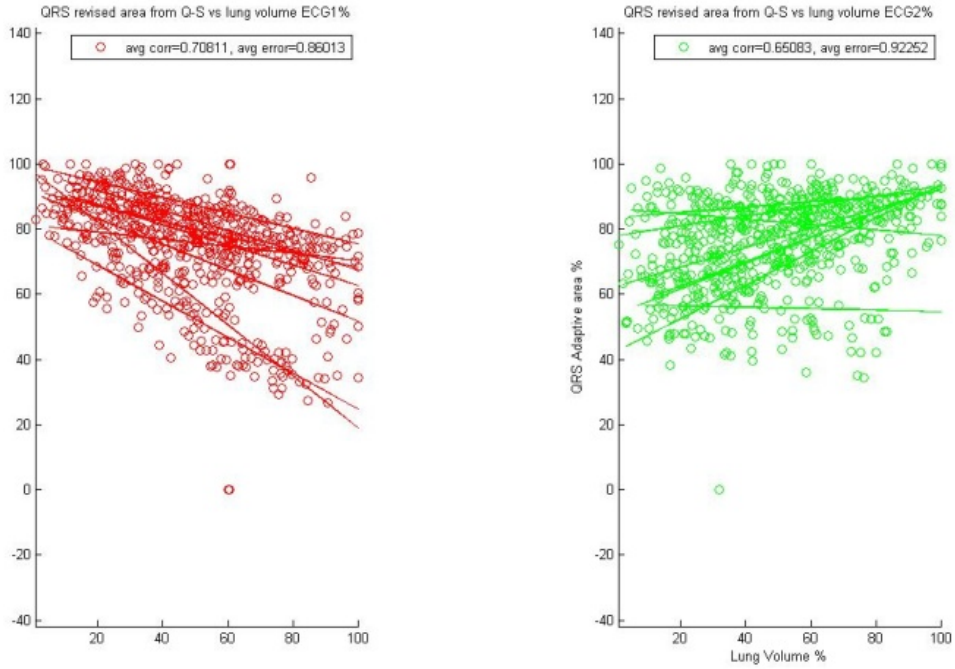

Figure 50: Q-SArea Correlation with lung volume

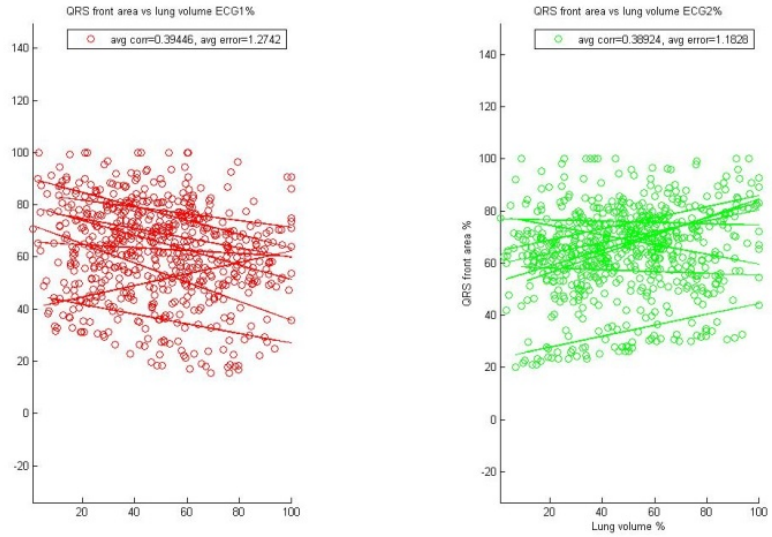

Figure 51: Q-RArea vs. lung volume at the R-Peak scattering pattern

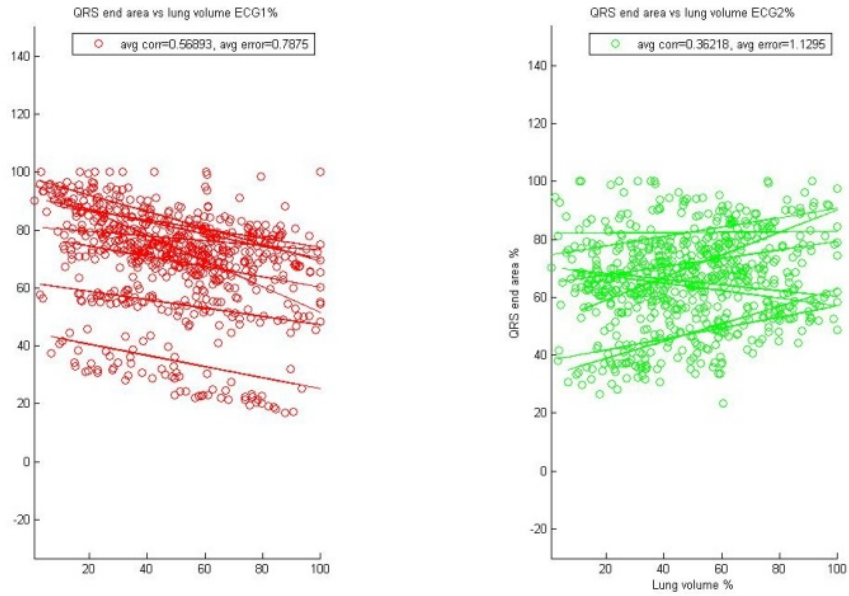

Figure 52: R-SArea vs. lung volume at the R-Peak scattering pattern

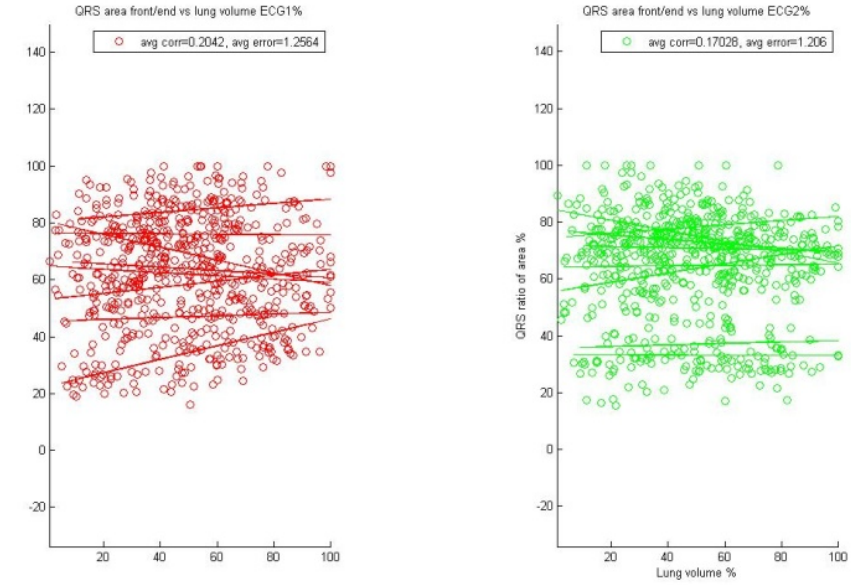

Figure 53: RatioArea vs. lung volume at the R-Peak scattering pattern

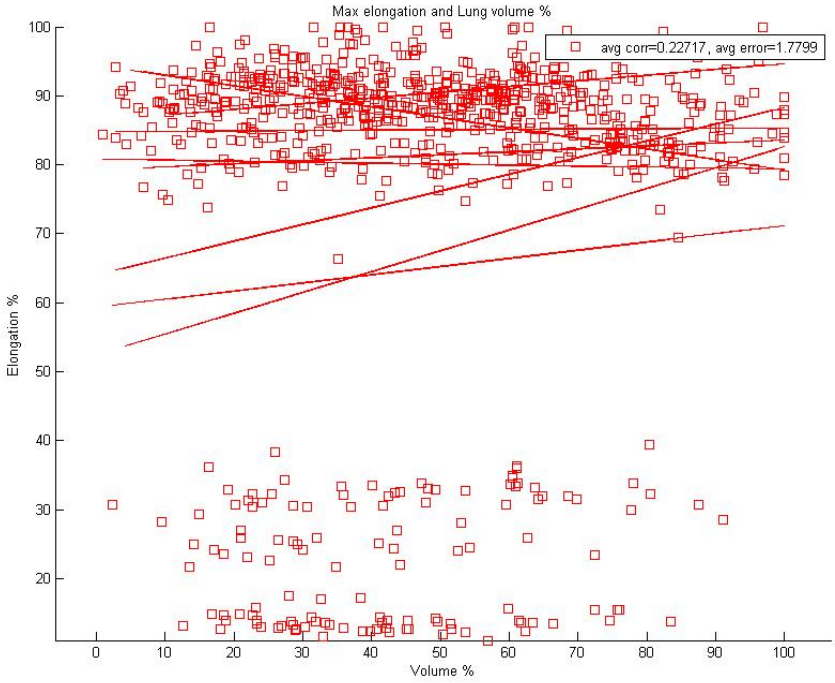

Figure 54: VECG Elongation correlation with lung volume

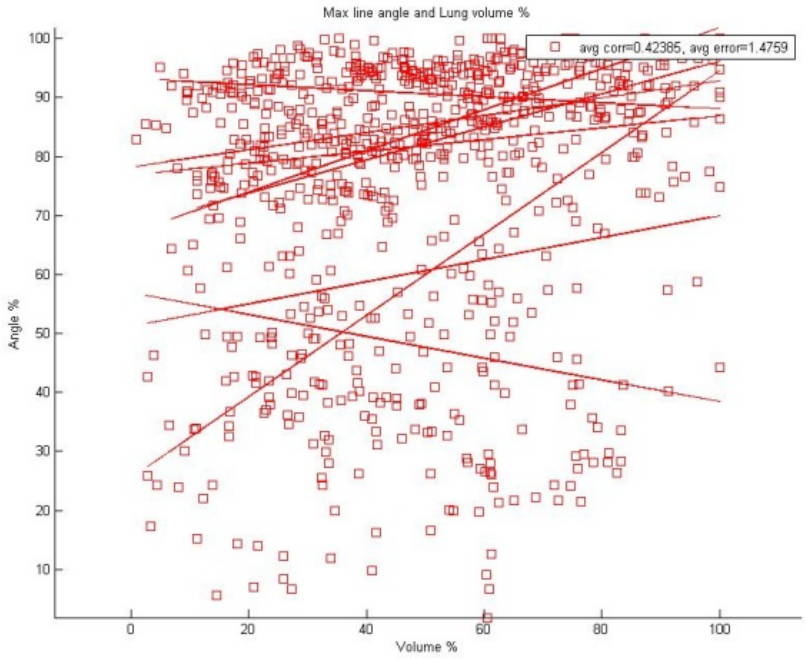

Figure 55: VECG Angle correlation with lung volume

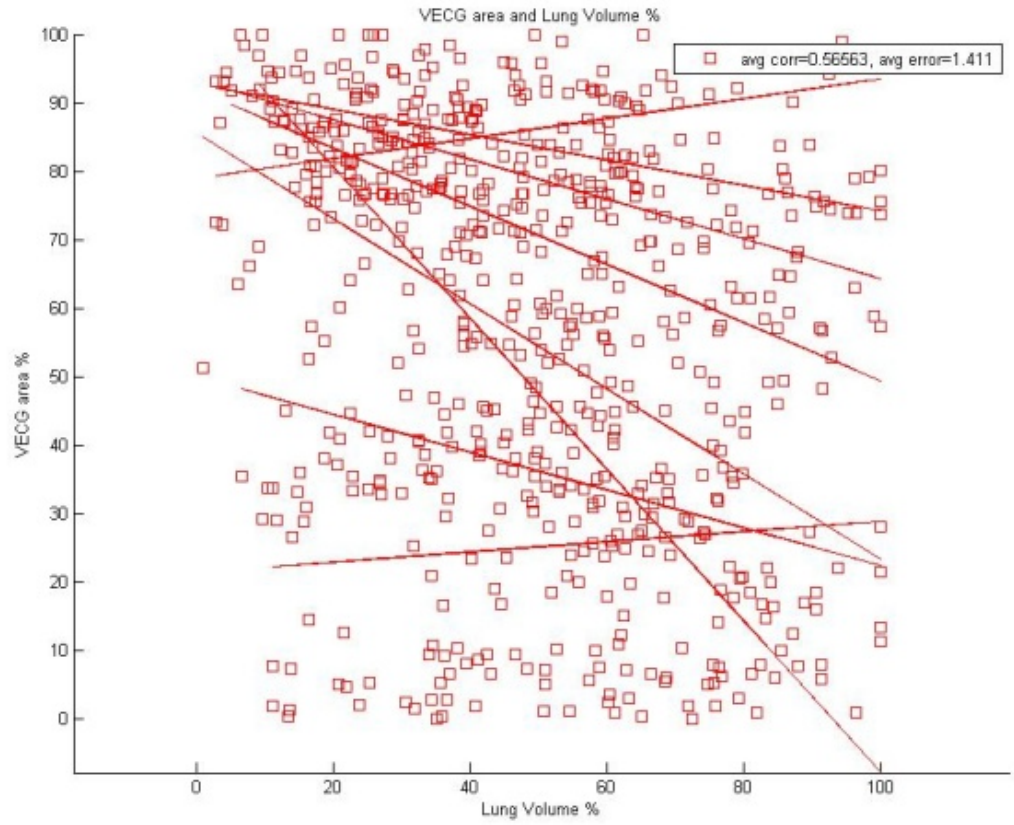

Figure 56: VECG area correlation with lung volume

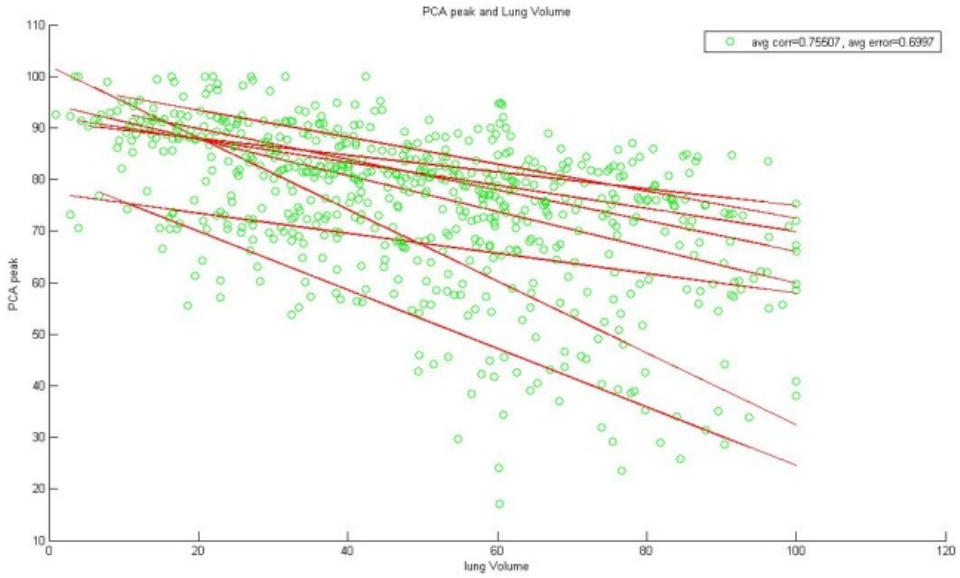

Figure 57: Correlation of PCA constructed R-Peak and Lung Volume of channel1 ECG

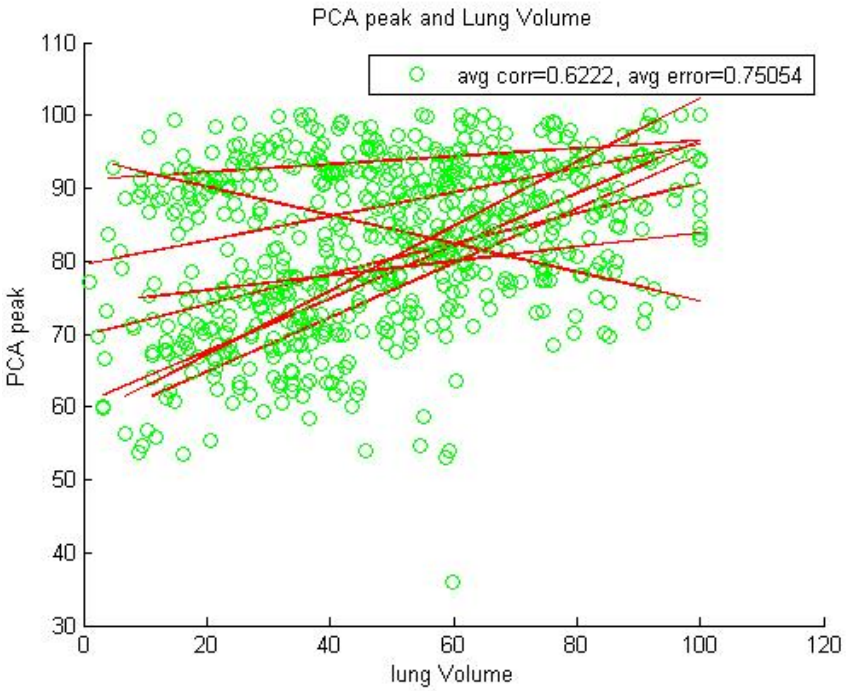

Figure 58: Correlation of PCA constructed R-Peak and Lung Volume of channel2 ECG

Lung Pressure Scattering Plots:

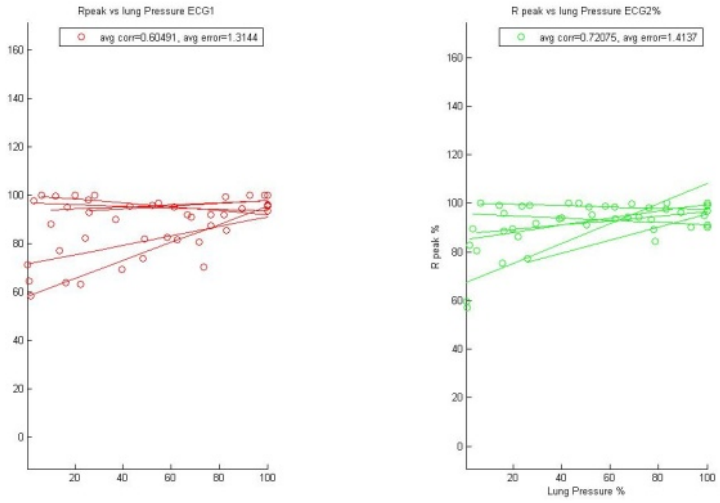

Figure 59: R-peak vs. lung pressure at min lung volume

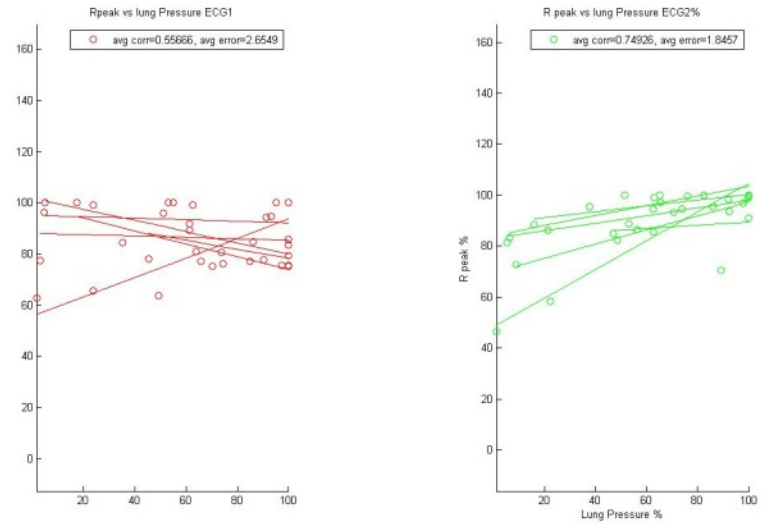

Figure 60: R-peak vs. lung pressure at 2nd lung volume

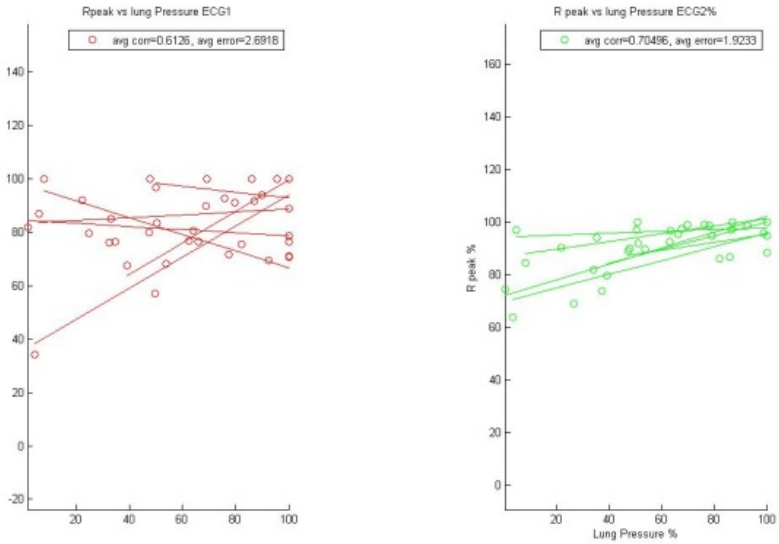

Figure 61: R-peak vs. lung pressure at 3rd lung volume

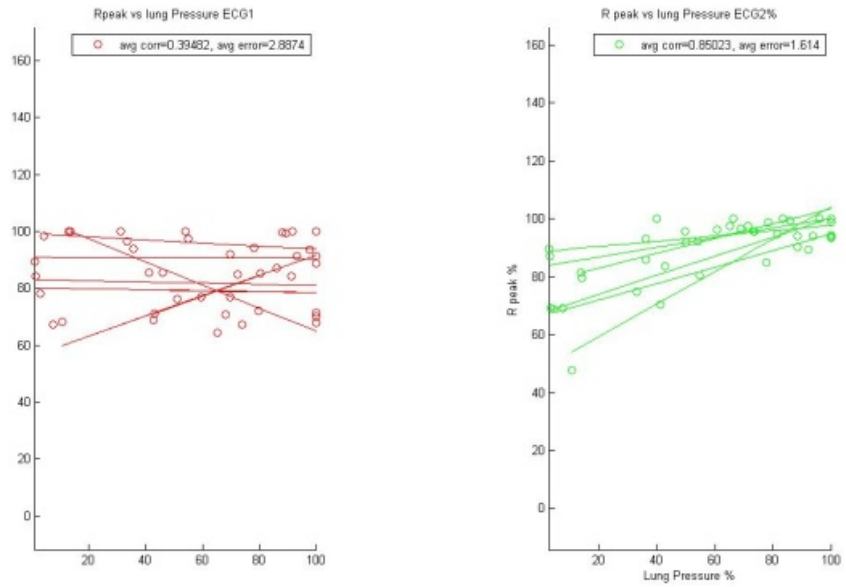

Figure 62: R-peak vs. lung pressure at 4th lung volume

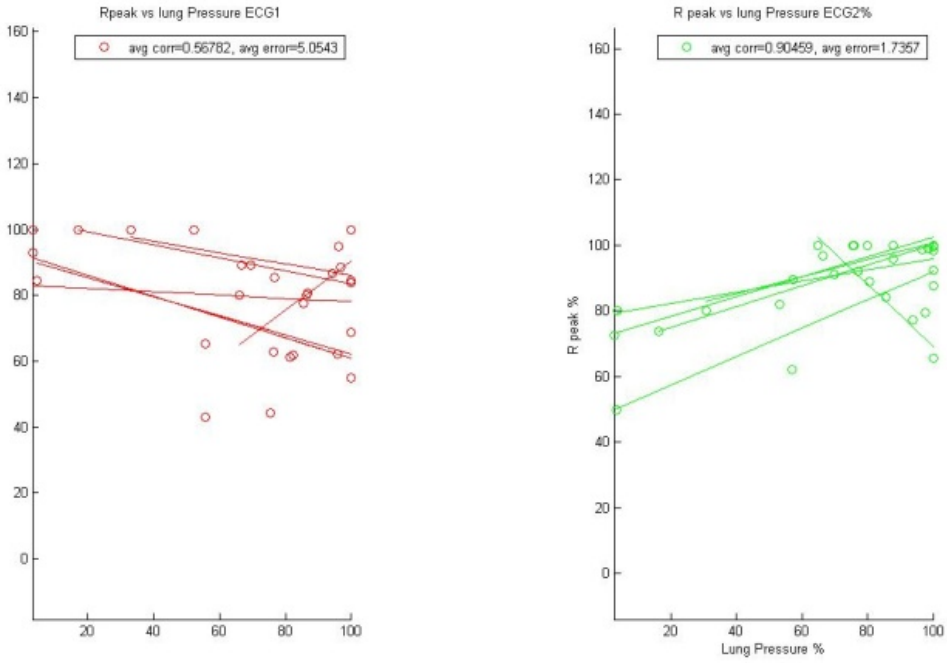

Figure 63: R-peak vs. lung pressure at max lung volume

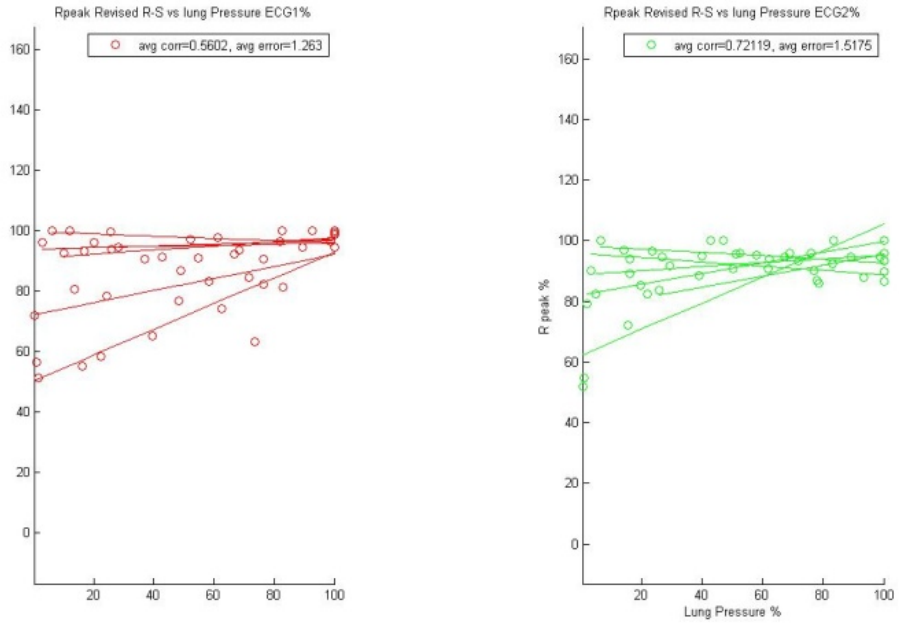

Figure 64: R-SPeak vs. lung pressure at min lung volume

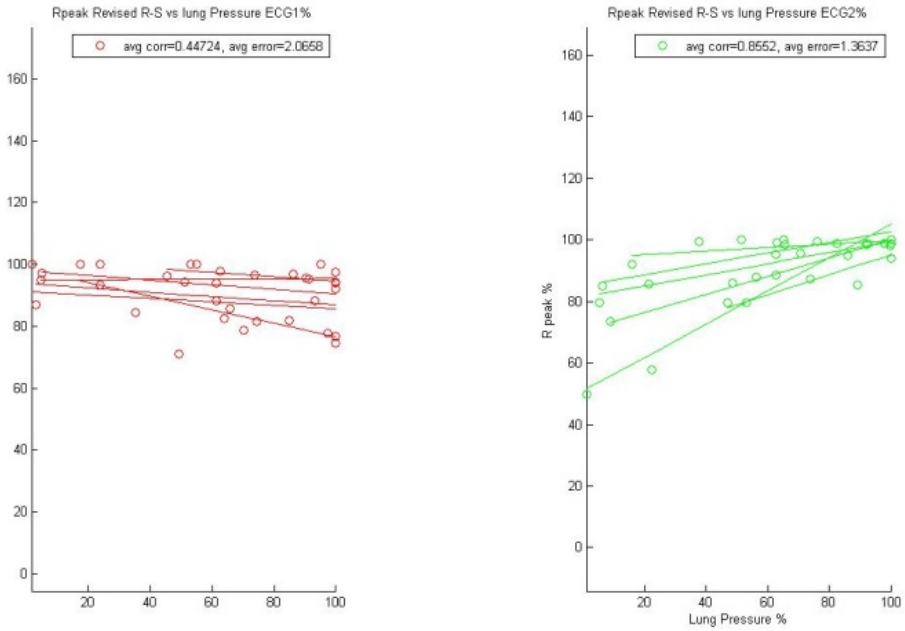

Figure 65: R-SPeak vs. lung pressure at 2nd lung volume

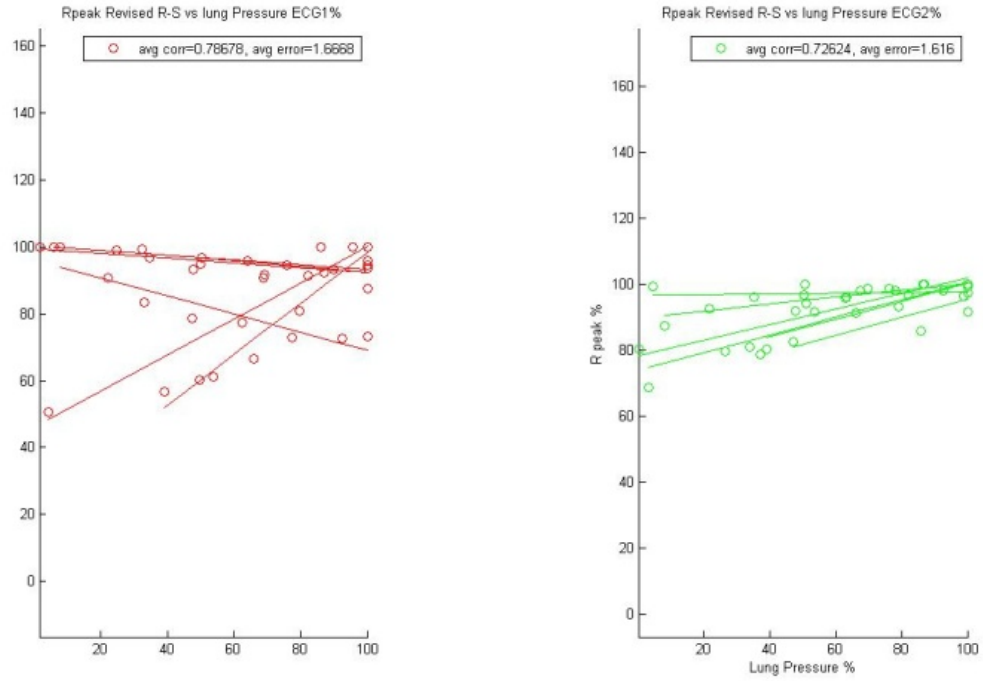

Figure 66: R-SPeak vs. lung pressure at 3rd lung volume

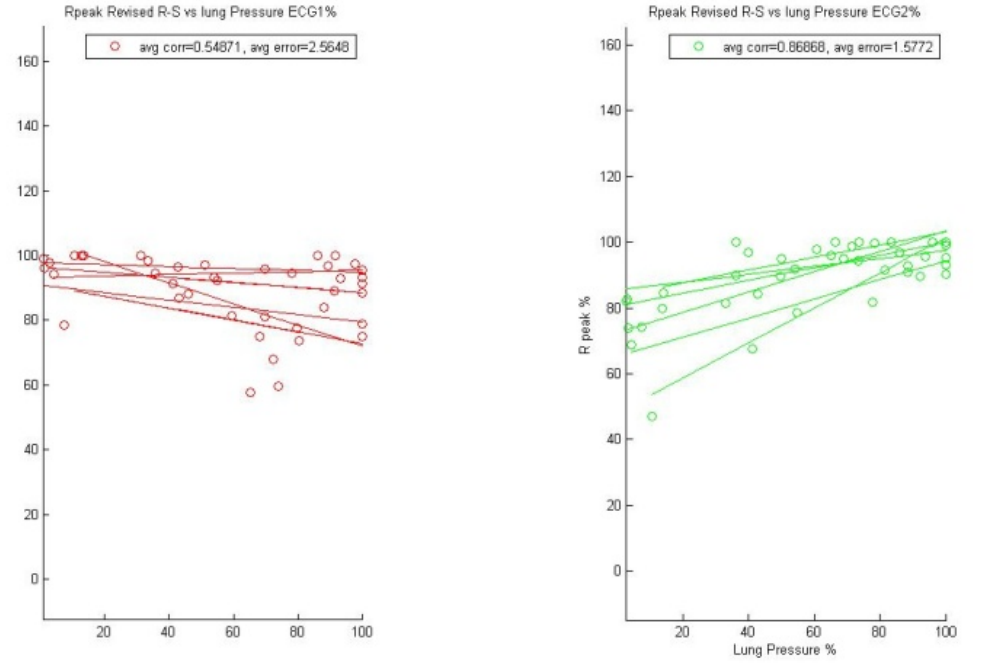

Figure 67: R-SPeak vs. lung pressure at 4th lung volume

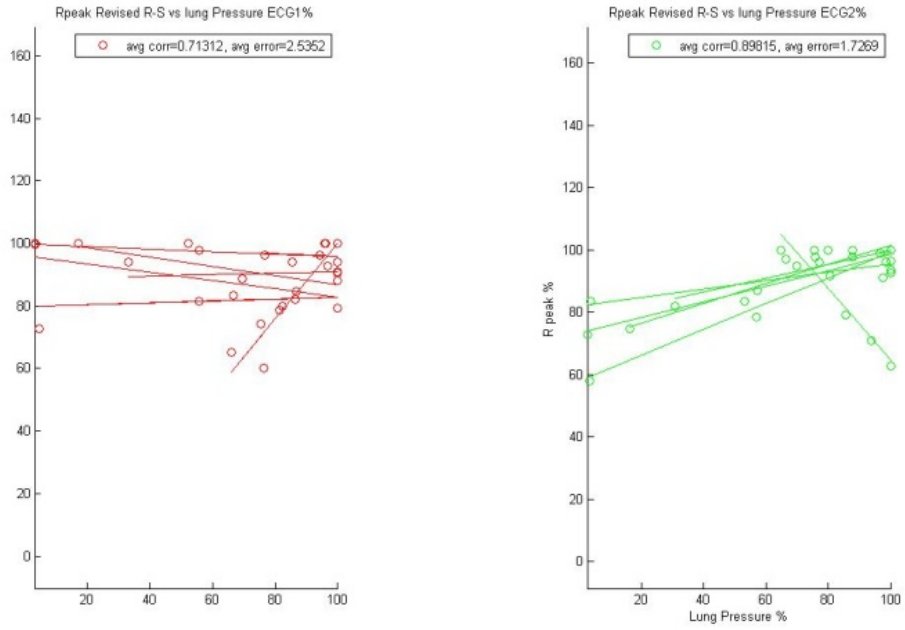

Figure 68: R-SPeak vs. lung pressure at max lung volume

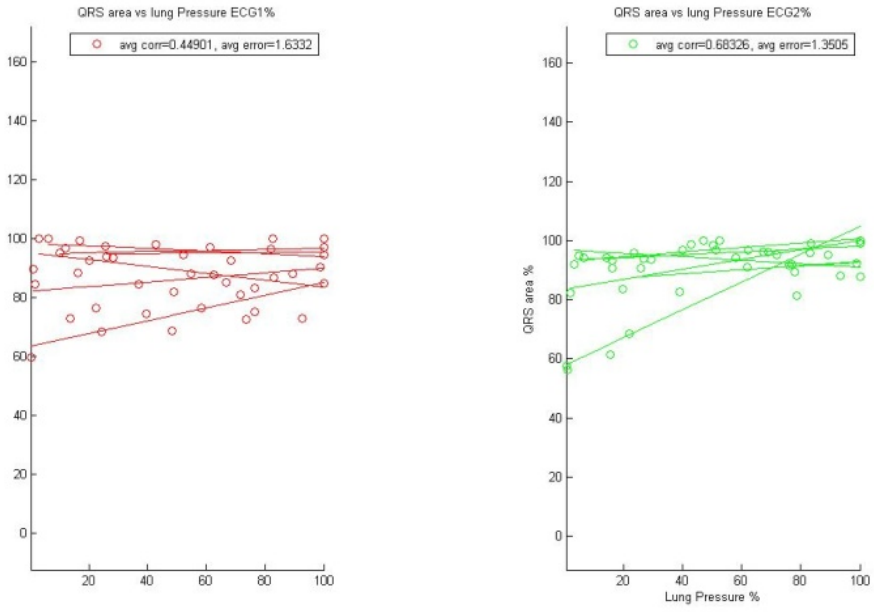

Figure 69: PulseArea vs. lung pressure at min lung volume

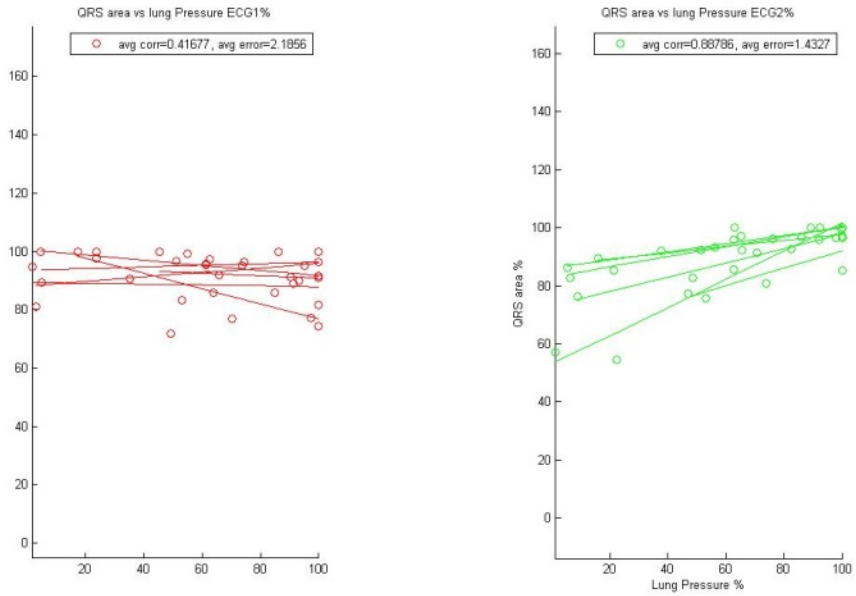

Figure 70: PulseArea vs. lung pressure at 2nd lung volume

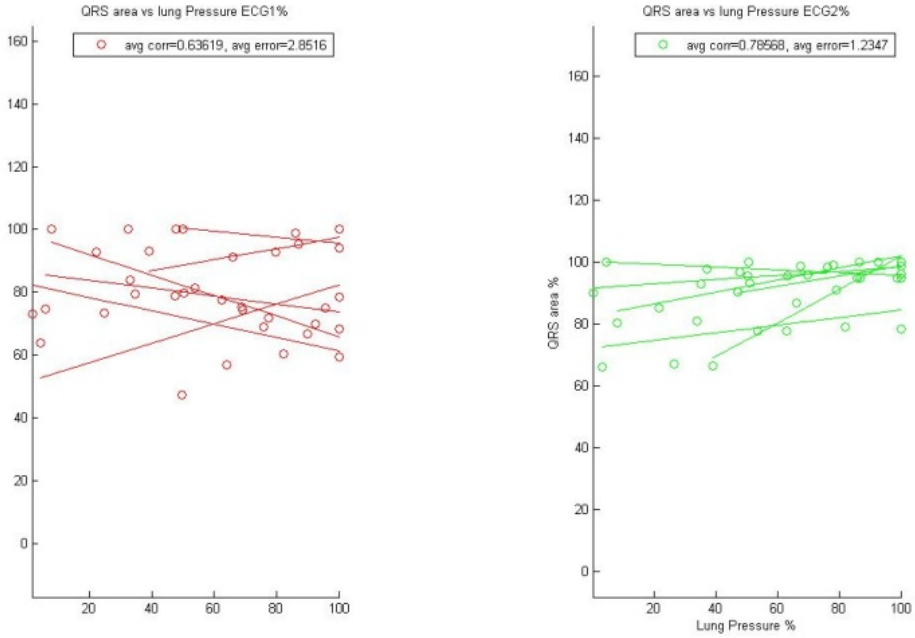

Figure 71: PulseArea vs. lung pressure at 3rd lung volume

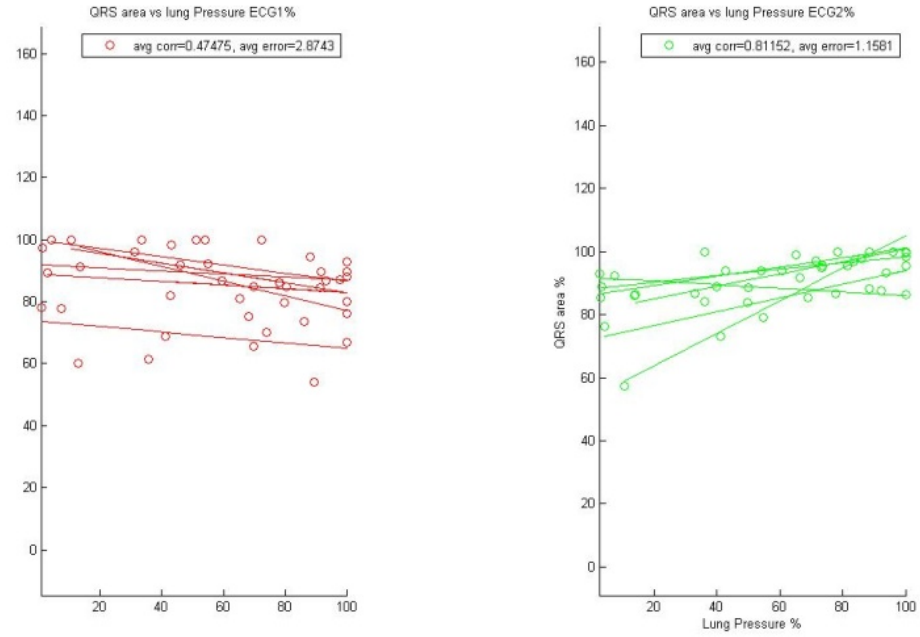

Figure 72: PulseArea vs. lung pressure at 4th lung volume

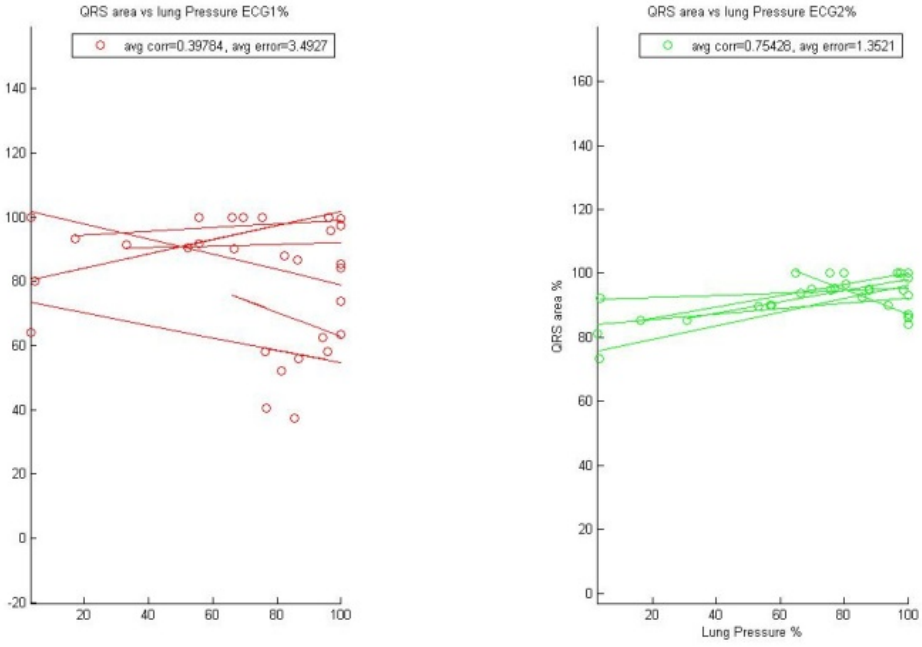

Figure 73: PulseArea vs. lung pressure at max lung volume

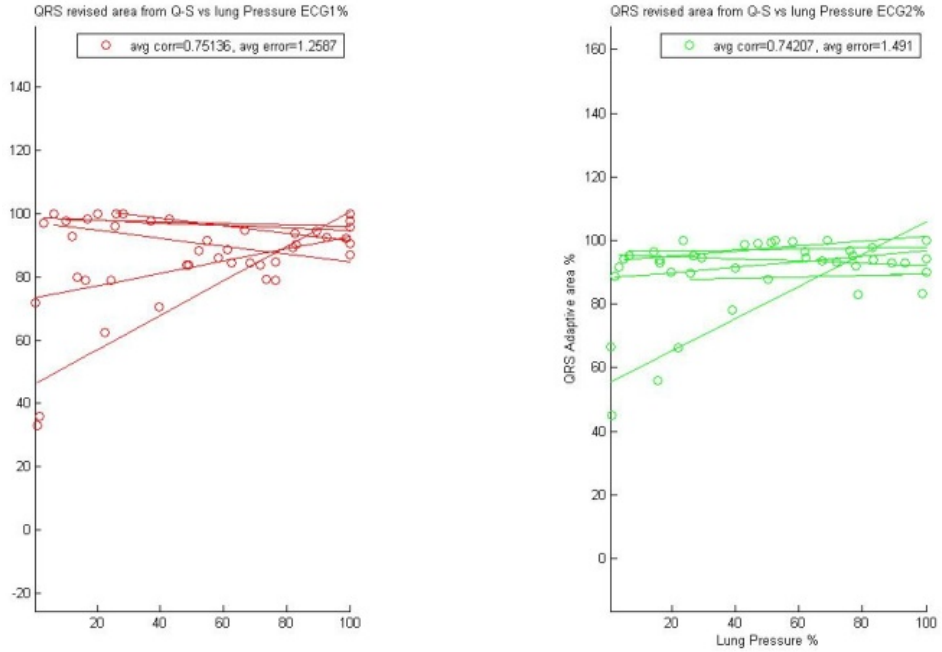

Figure 74: Q-SArea vs. lung pressure for min lung volume

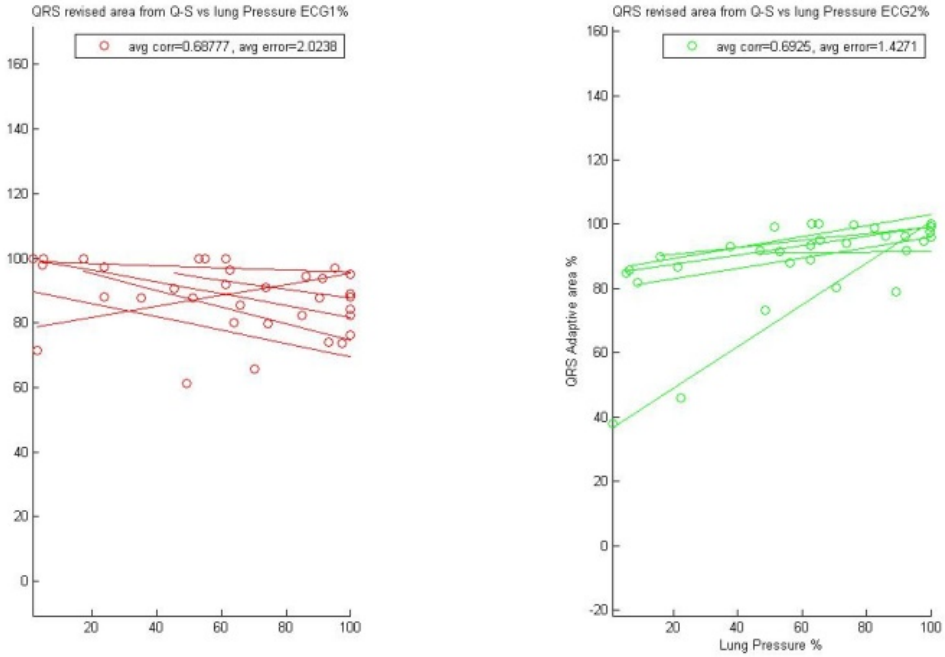

Figure 75: Q-SArea vs. lung pressure at 2nd lung volume

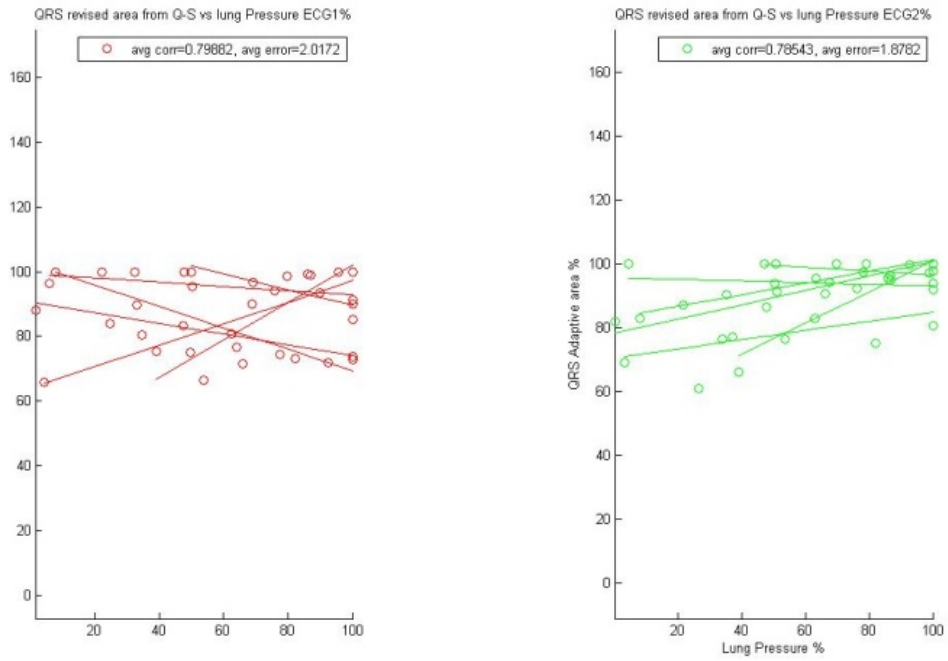

Figure 76: Q-SArea vs. lung pressure at 3rd lung volume

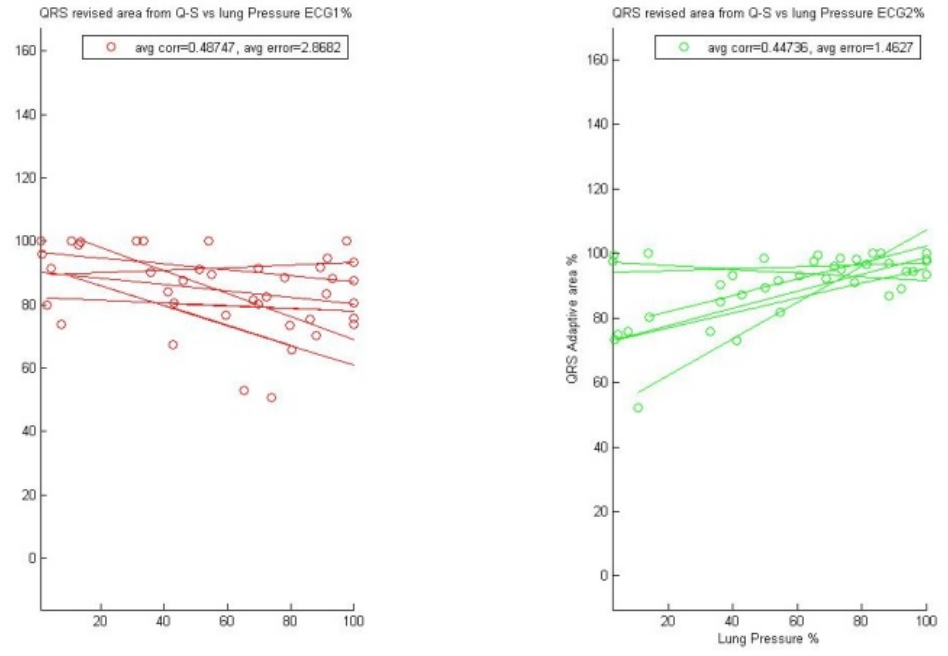

Figure 77: Q-SArea vs. lung pressure at 4th lung volume

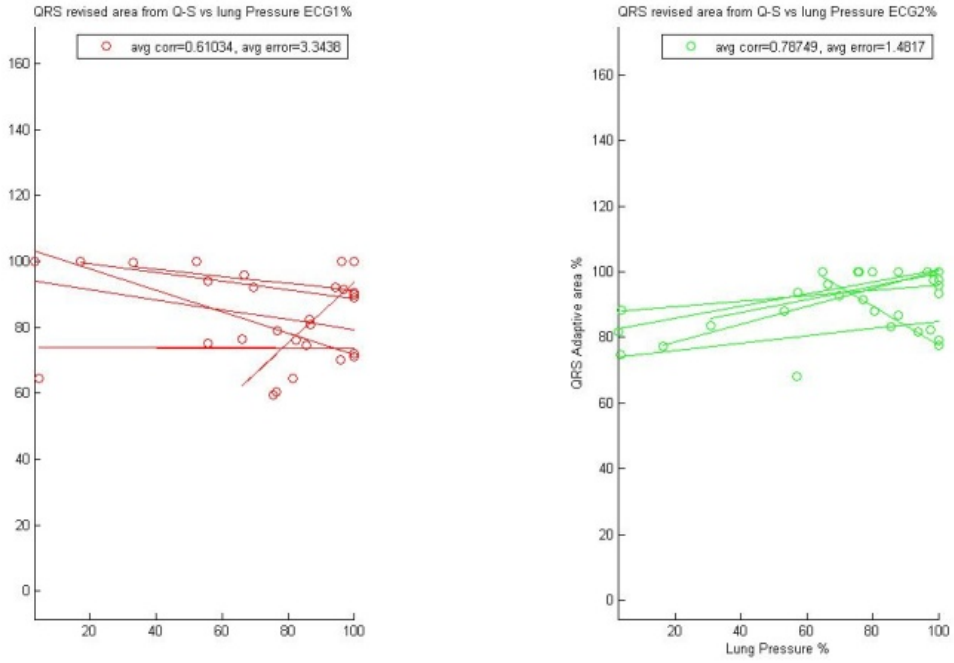

Figure 78: Q-SArea vs. lung pressure at max lung volume

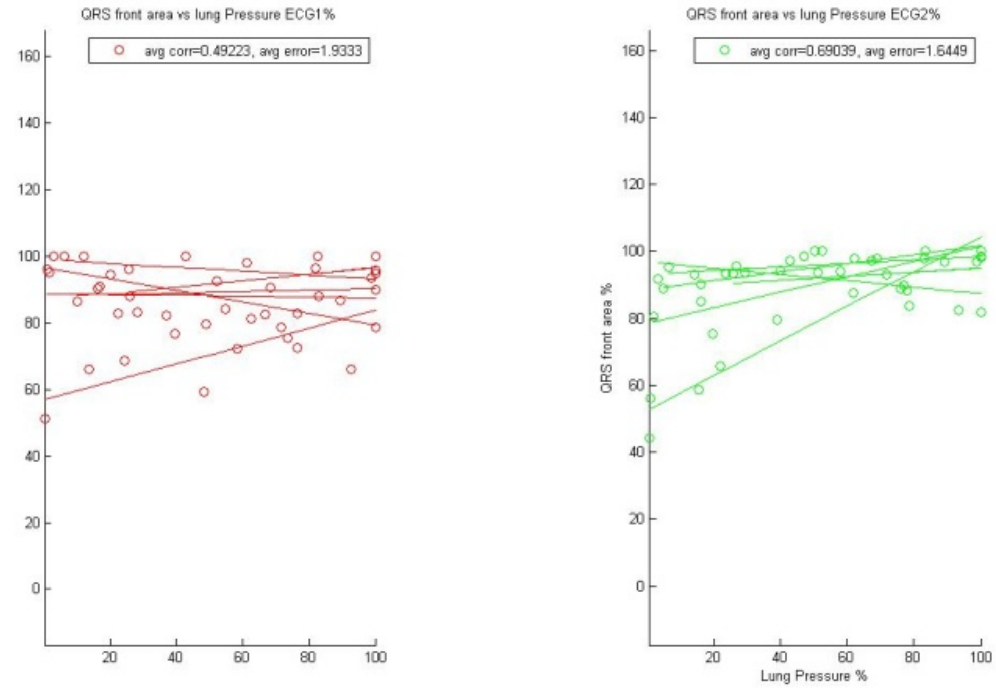

Figure 79: Q-RArea front area vs. lung pressure at min lung volume

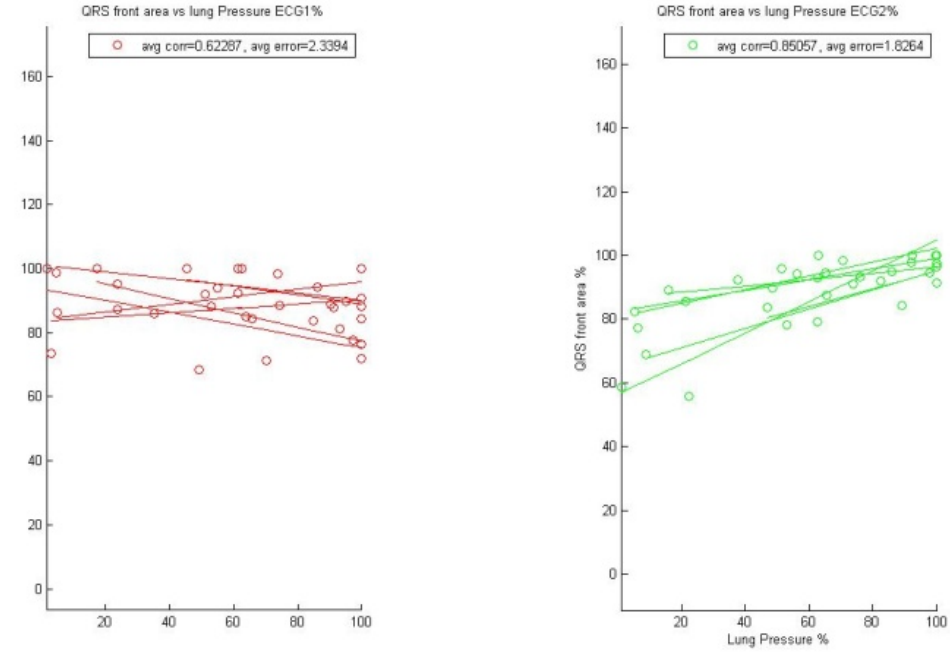

Figure 80: Q-RArea front area vs. lung pressure at 2nd lung volume

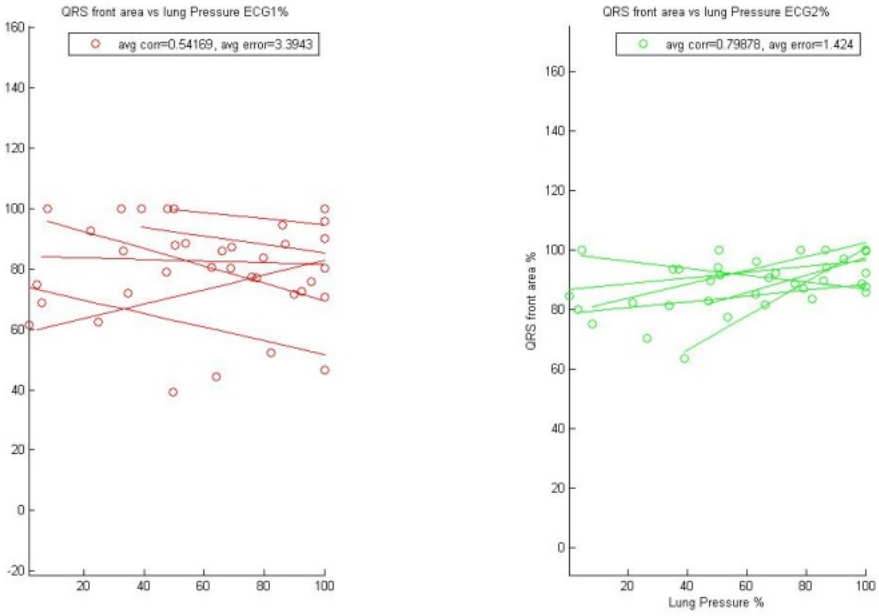

Figure 81: Q-RArea front area vs. lung pressure at 3rd lung volume

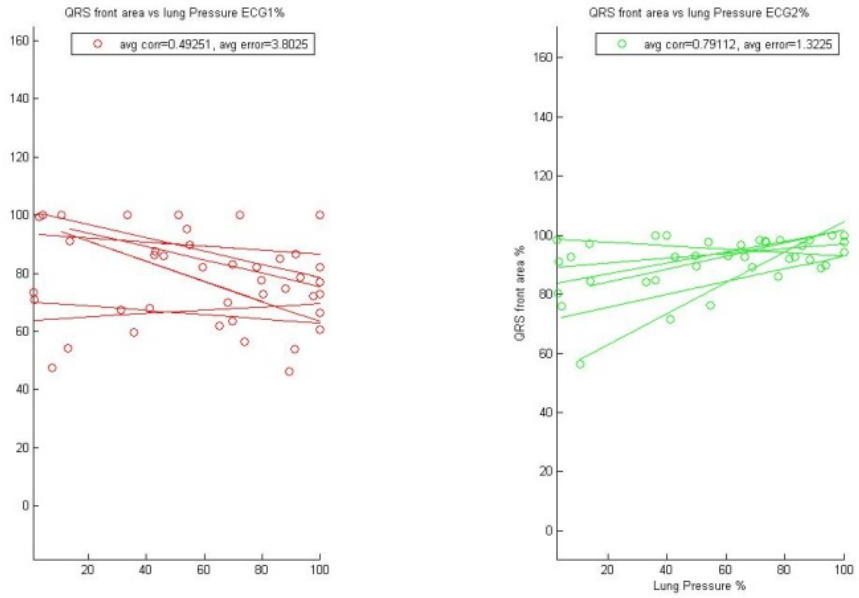

Figure 82: Q-RArea front area vs. lung pressure at 4th lung volume

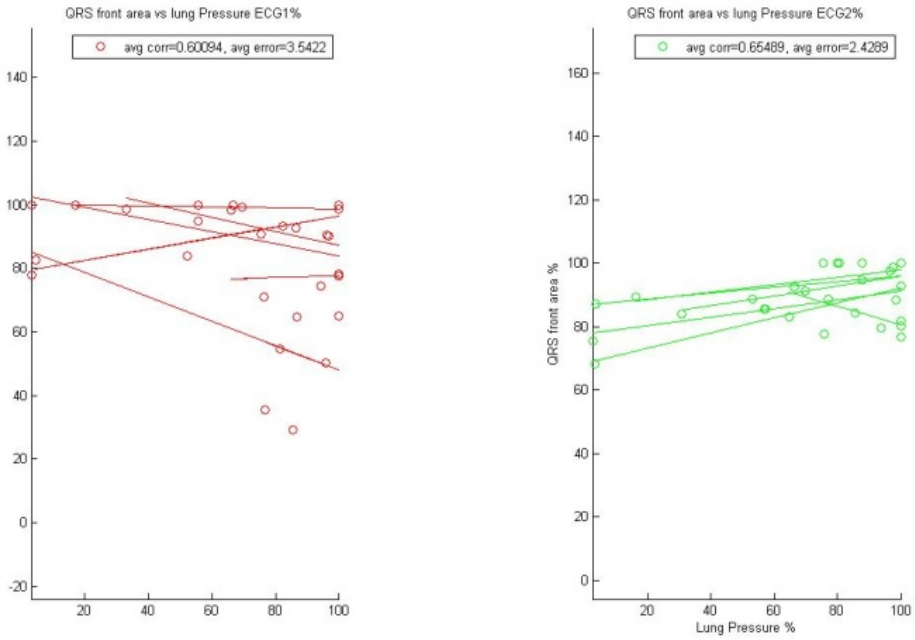

Figure 83: Q-RArea front area vs. lung pressure at max lung volume

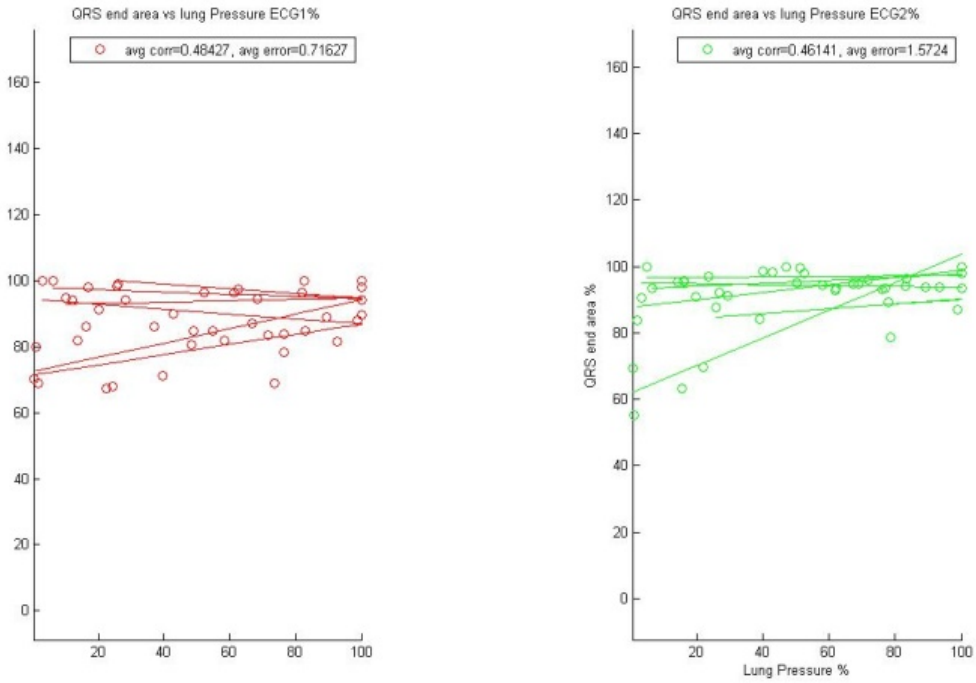

Figure 84: R-SArea end area vs. lung pressure at min lung volume

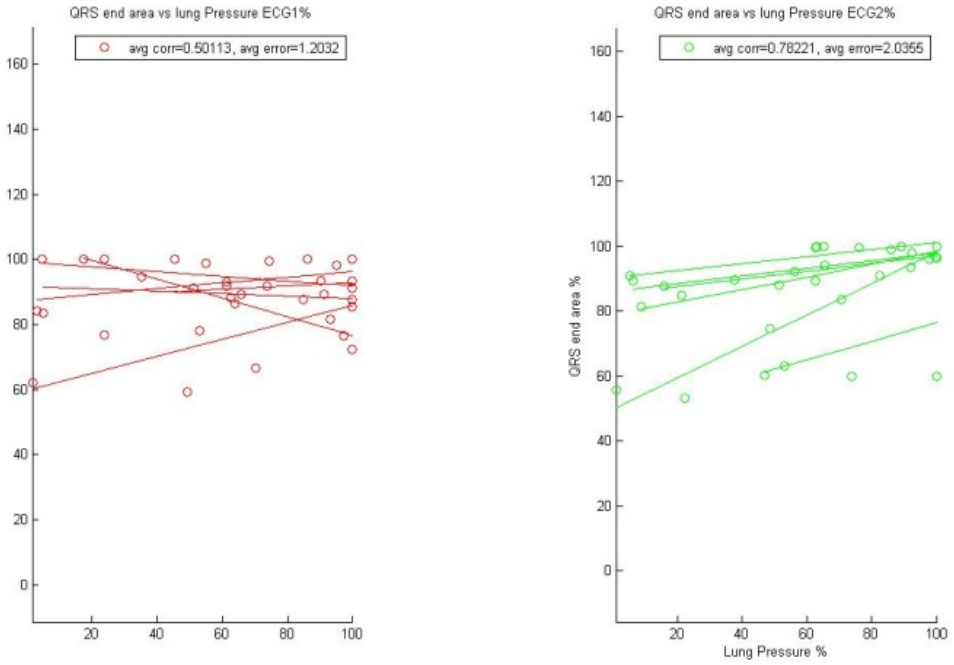

Figure 85: R-SArea end area vs. lung pressure at 2nd lung volume

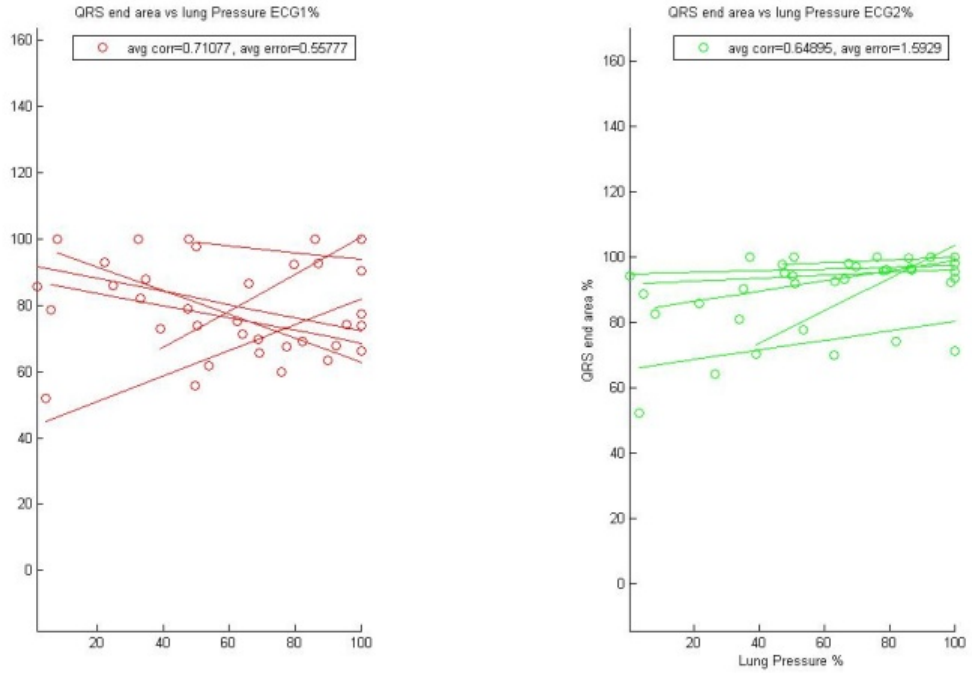

Figure 86: R-SArea end area vs. lung pressure at 3rd lung volume

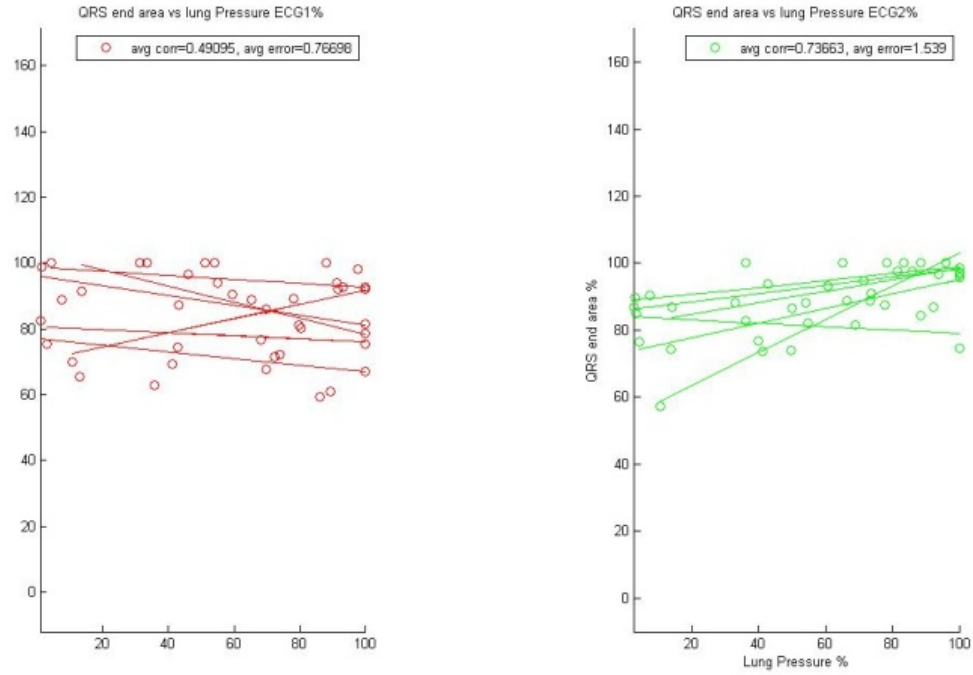

Figure 87: R-SArea end area vs. lung pressure at 4th lung volume

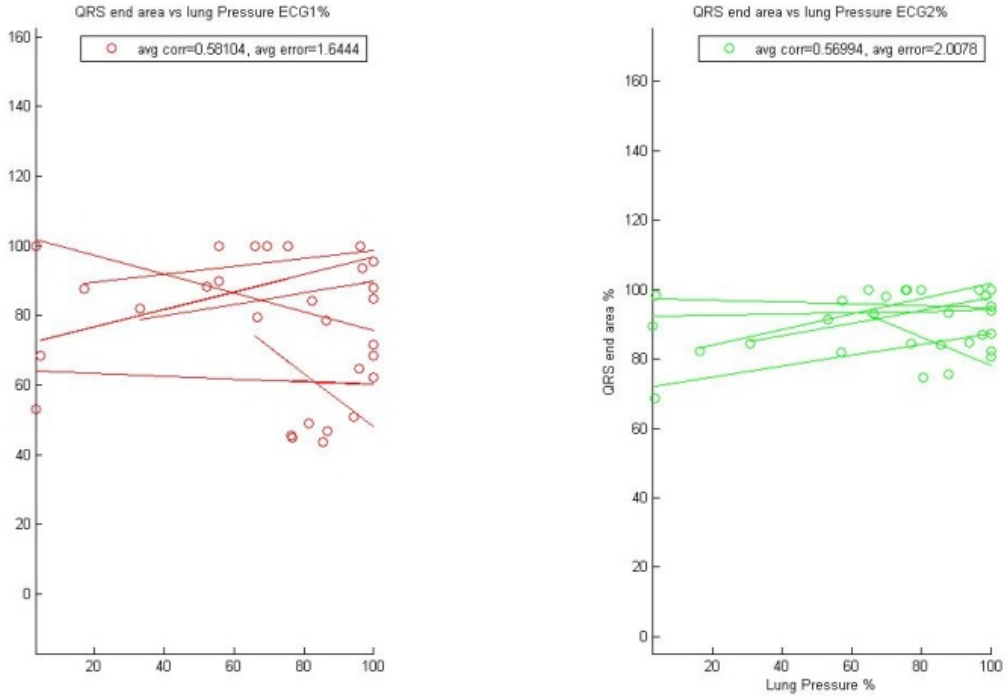

Figure 88: R-SArea end area vs. lung pressure at max lung volume

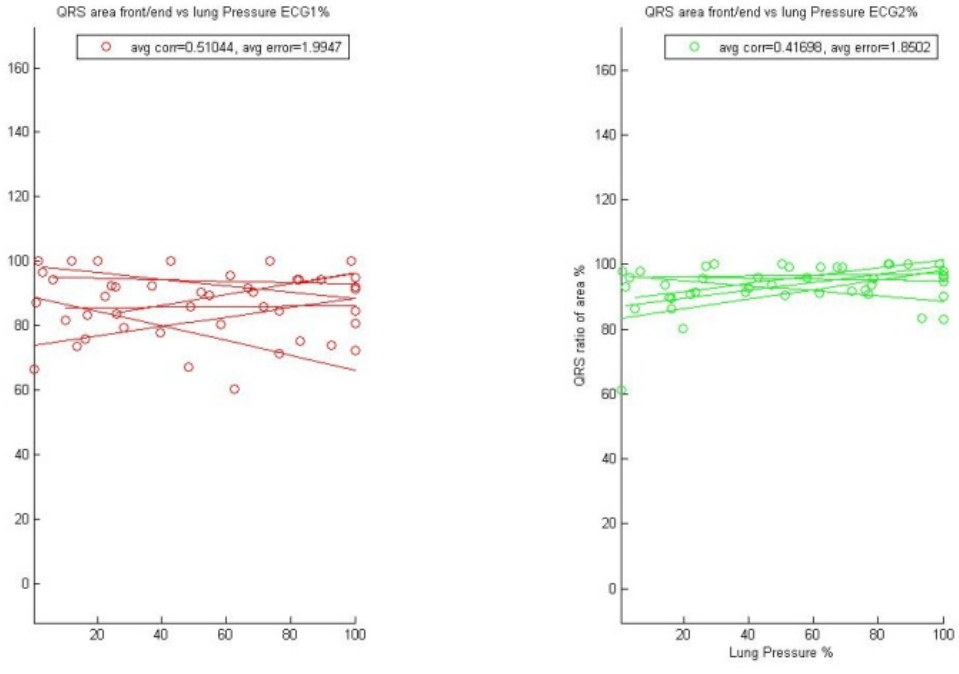

Figure 89: RatioArea vs. lung pressure at min lung volume

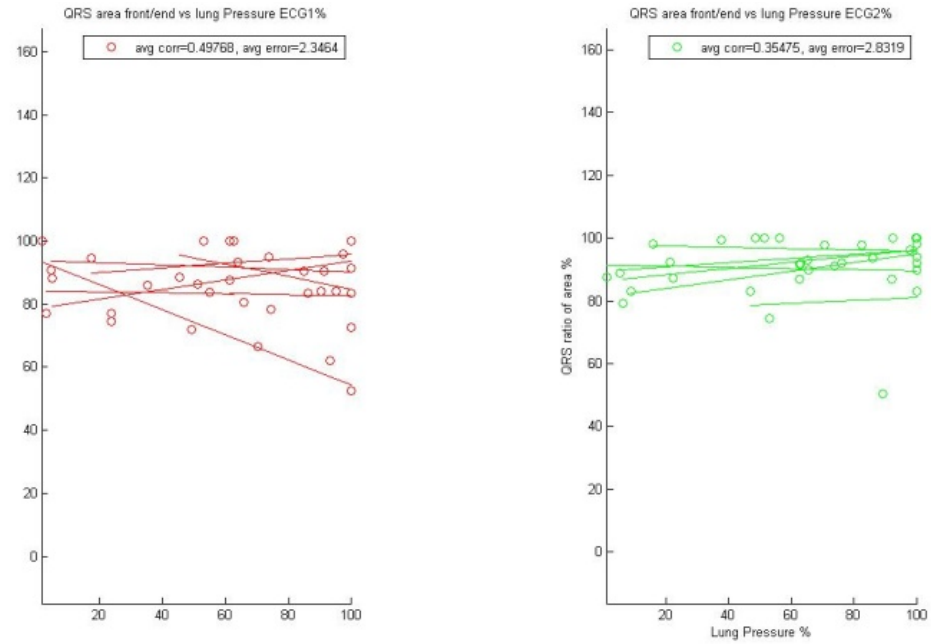

Figure 90: RatioArea vs. lung pressure at 2nd lung volume

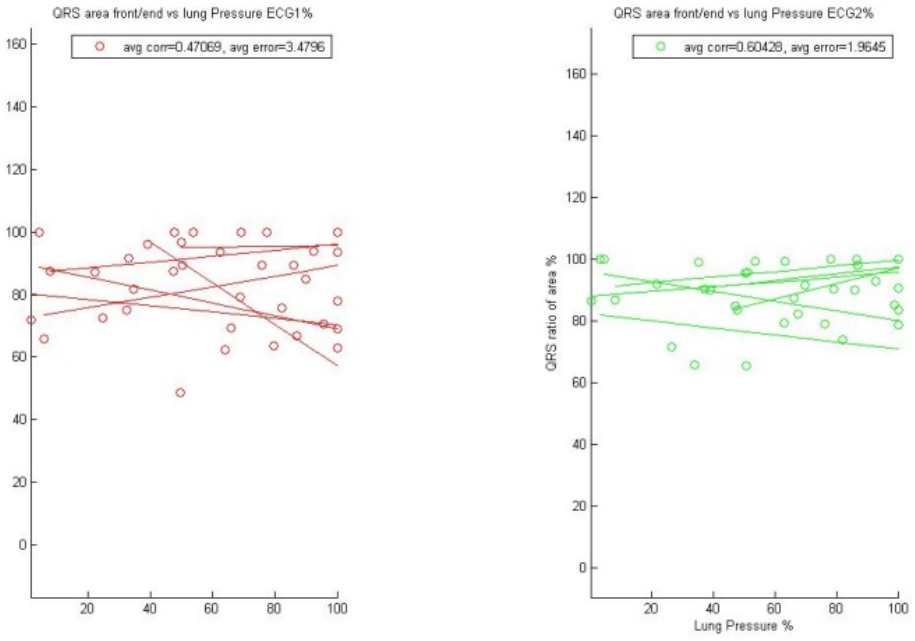

Figure 91: RatioArea area vs. lung pressure at 3rd lung volume

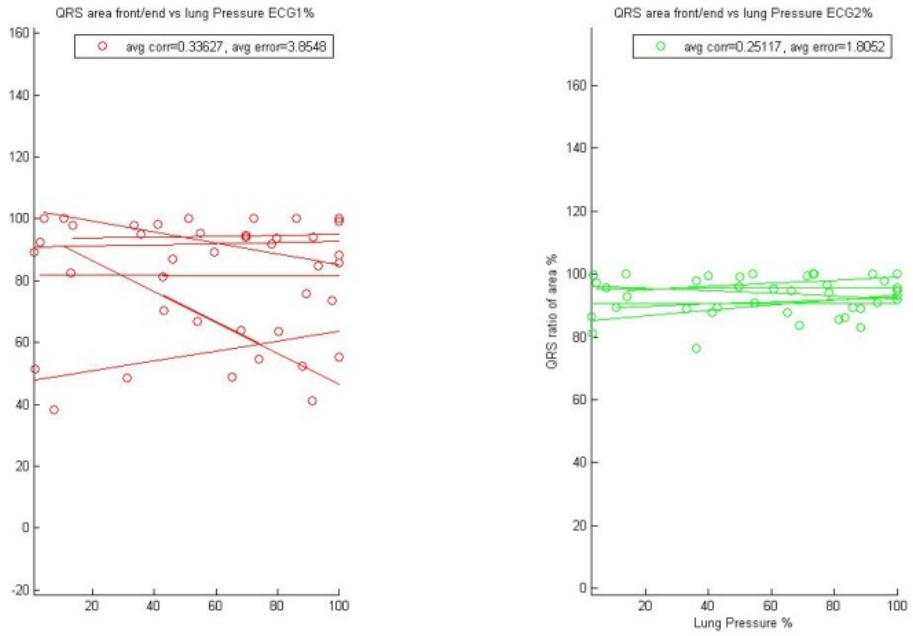

Figure 92: RatioArea vs. lung pressure at 4th lung volume

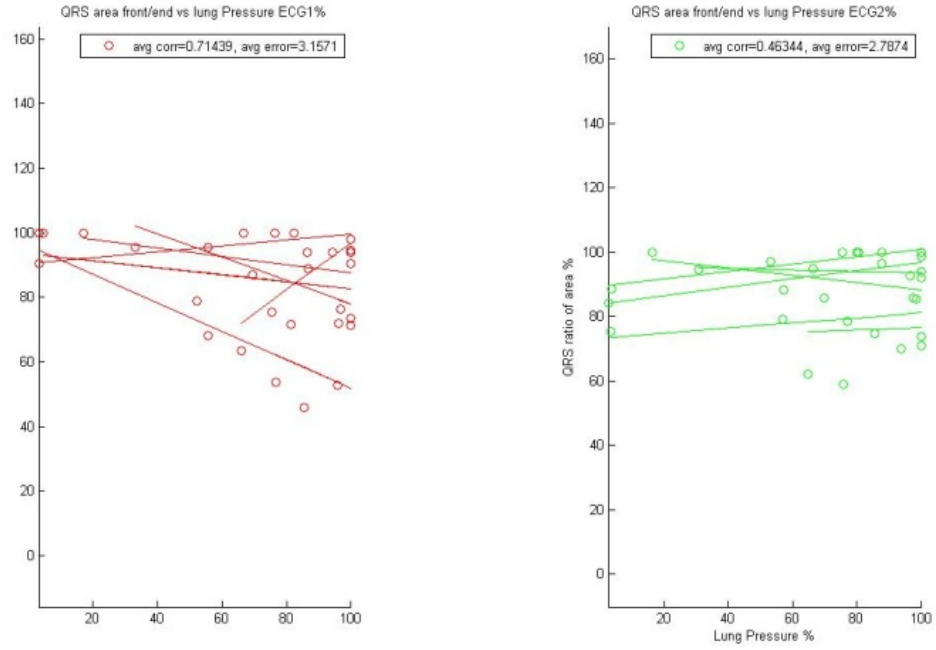

Figure 93: RatioArea vs. lung pressure at max lung volume

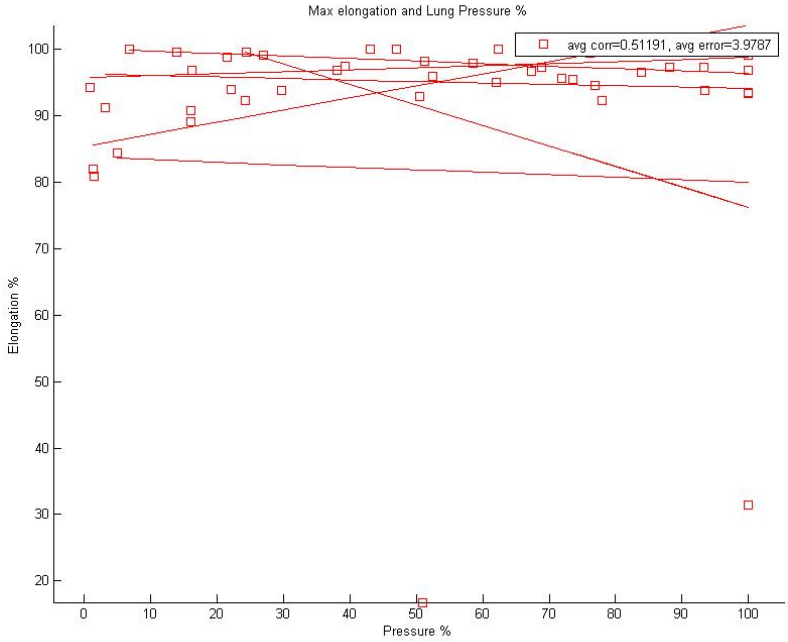

Figure 94: VECG Elongation Length vs. lung pressure at min lung volume

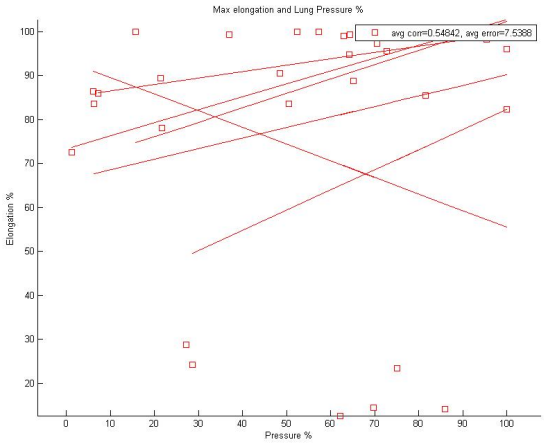

Figure 95: VECG Elongation Length vs. lung pressure at 2nd lung volume

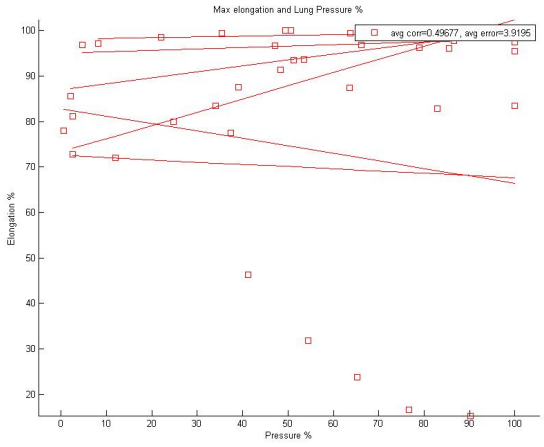

Figure 96: VECG Elongation Length vs. lung pressure at 3rd lung volume

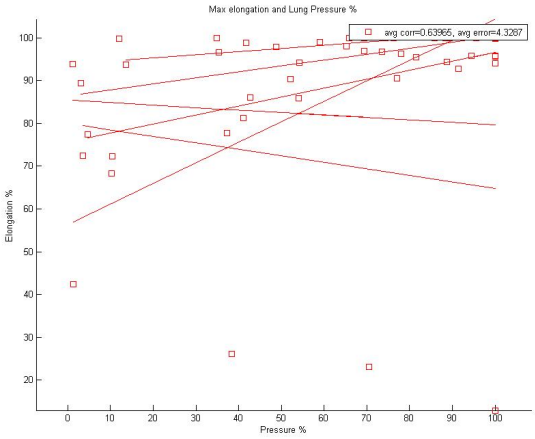

Figure 97: VECG Elongation Length vs. lung pressure at 4th lung volume

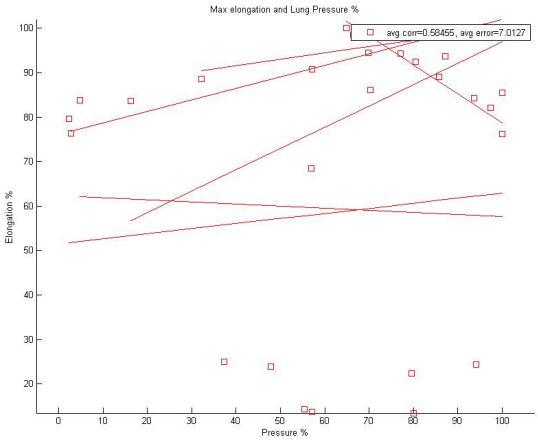

Figure 98: VECG Elongation Length vs. lung pressure at max lung volume

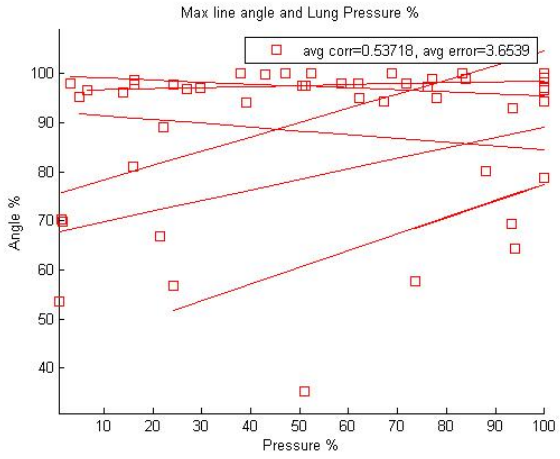

Figure 99: VECG angle vs. lung pressure at min lung volume

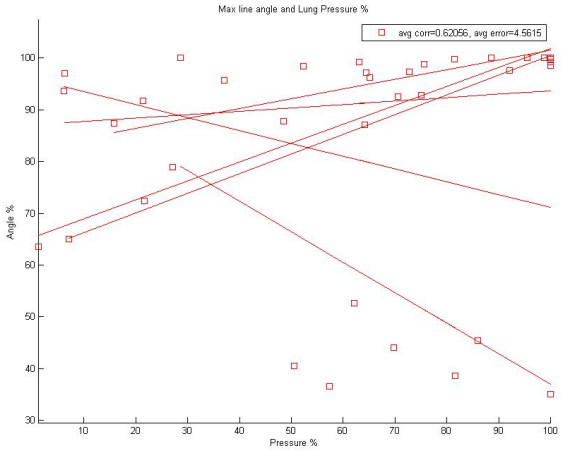

Figure 100: VECG angle vs. lung pressure at 2nd lung volume

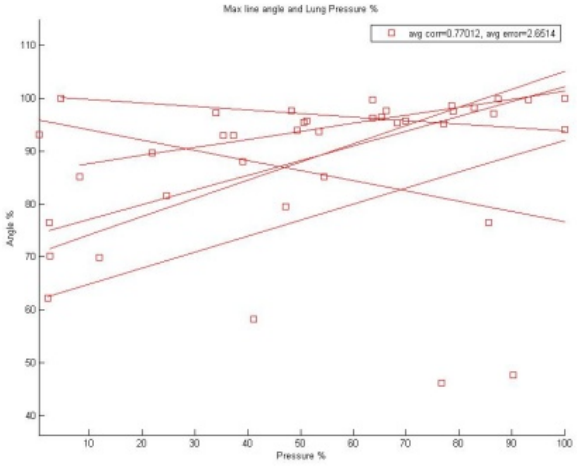

Figure 101: VECG angle vs. lung pressure at 3rd lung volume

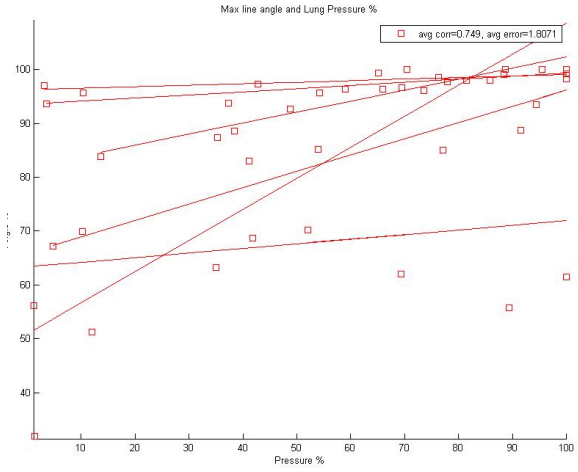

Figure 102: VECG angle vs. lung pressure at 4th lung volume

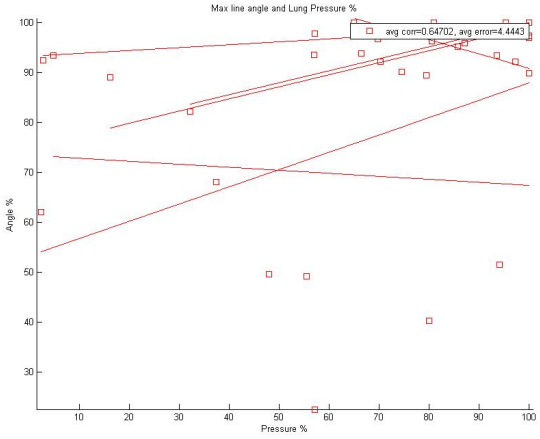

Figure 103: VECG angle vs. lung pressure at max lung volume

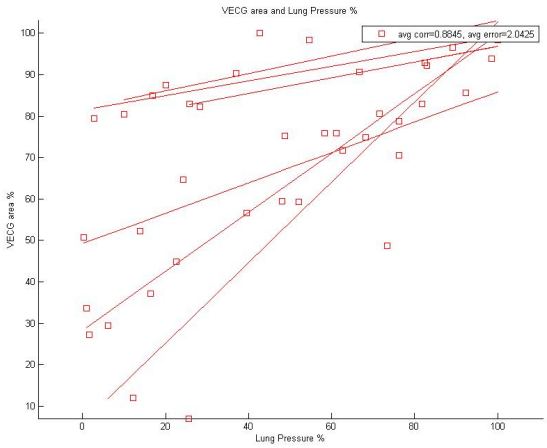

Figure 104: VECG area vs. lung pressure at min lung volume

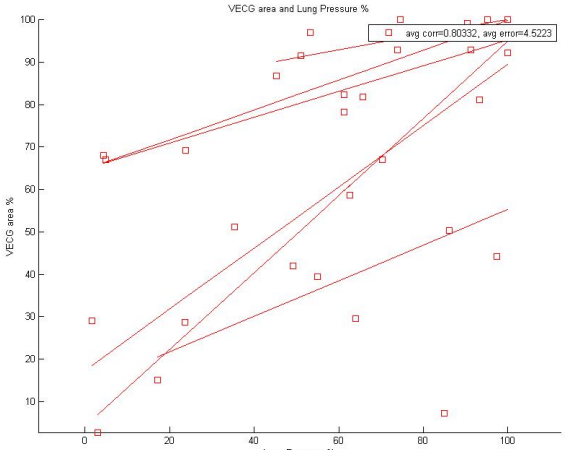

Figure 105: VECG area vs. lung pressure at 2nd lung volume

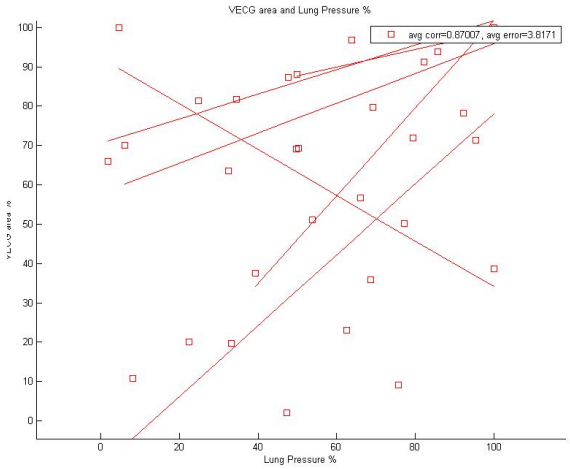

Figure 106: VECG area vs. lung pressure at 3rd lung volume

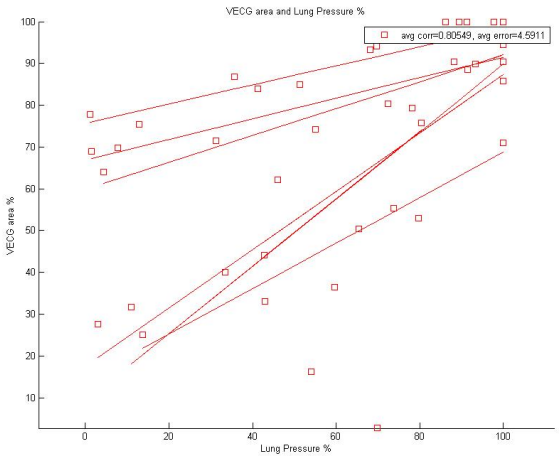

Figure 107: VECG area vs. lung pressure at 4th lung volume

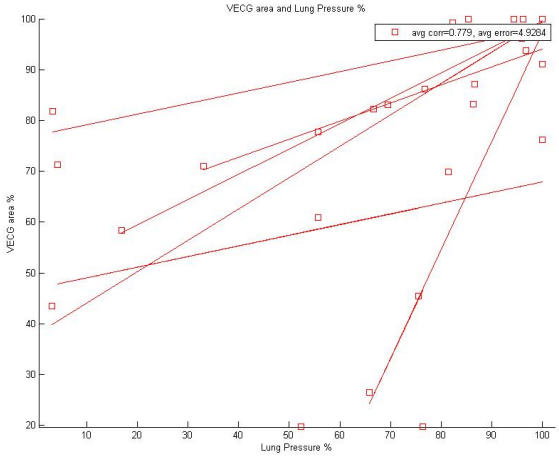

Figure 108: VECG area vs. lung pressure at max lung volume

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