BCG Measurements in Beds

Description of applications and the Murata approach

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Introduction and Background

There exists a variety of ways to monitor the functionality of the heart. An Electrocardiogram (ECG) reveals the electrical functionality, with ultrasound a cardiologist can monitor valve operation and flow, with blood pressure measurement the resulting blood pressure or pressure wave, and with Ballistocardiography (BCG) you measure the mechanical pumping of the heart. BCG gives both the time and relative Stroke Volume (SV) of every heartbeat [1].

The advantage of ECG is that it can detect failures in the electrical operation of the heart, such as arrhythmia, signal delay or blocking or abnormal polarization or depolarization. Its limitations include the requirement for attached electrodes and lack of information of the real pumping of the heart.

BCG on the other hand, with the sensor in the bed, is non-intrusive and maintenance free, and in this way suitable for long-term nocturnal measurements. Thus, it is an excellent tool to measure recovery and sleep quality [2], but can also reveal e.g. potential sleep apnoea or nocturnal arrhythmia. You can combine the BCG measurement in the bed with e.g. a daytime Blood Pressure Wave (BPW) measurement with a bracelet. In this way you will have 24/7 monitoring of the status of your heart and autonomous nervous system. Non-invasive BPW measurement is an excellent tool, as well for monitoring the function of the heart, as for that of the blood vessels [13].

A good sleep is important for everyone to prevent from a large variety of diseases and for one's life expectancy. The positive effects are not limited to conditions related to the heart or blood vessel functionality, but good sleep is also important e.g. for mental wellness and even to prevent from types of cancer. For seniors there is a need for continuous monitoring of vital signs, both in domestic homes and elderly care to increase wellness, enable independent living, and improve patient security and save hands and costs, also as patients could exit the hospital earlier and stay outside it in a safe way. For athletes recovery and good sleep are decisive in reaching good training and competition results. Optimum training and recovery make top athletes.

Heartbeat and respiration parameters are excellent indicators for one's general condition and life expectancy [3]. They do not only measure the condition of the heart, but of the entire body through the autonomous nervous system and indicate many pathological conditions, like Stroke Volume Variation (SVV) as a measure of body fluid condition [4].

BCG Signal

The BCG signal is the recoil caused by the blood flowing into the aorta, the aorta turning and the blood pressure pulse continuing into the arteries [1]. This motion is mainly along the longitudinal axis of the body and the acceleration amplitude is typically of the order of 1mg (1cm/s^2). A typical BCG signal can be seen in **Figure 1**. There are large variations in spring constants and damping factors in beds resulting in different signal amplitude modulation and attenuation time constants (d->e->... in **Figure 1**).

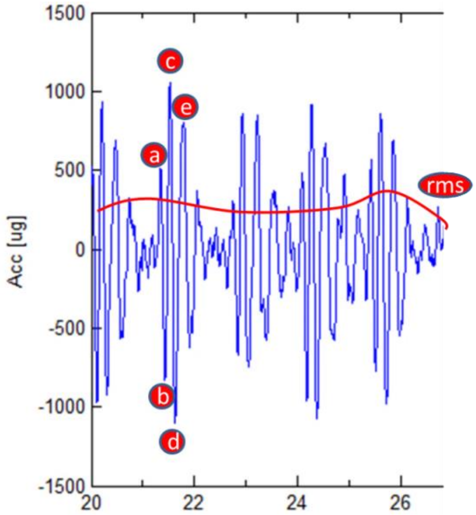


Figure 1: Typical BCG signal

Reported Output Parameters

The Murata BCG sensor measures the time and strength of every heartbeat as well as provides measures of ones activity in the bed. It then calculates and reports once per second time, Heart Rate

(HR), Respiration Rate (RR), relative Stroke Volume (SV), high frequency Heart Rate Variability (HRV), FFT indicator (FFT_I), bed occupancy & movement status (ST) deduced from FFT_I, and the detected raw beat to beat times (tB2B) in reverse chronological order (B2B, B2B' & B2B"). We have reserved three parameters for tB2B, as there might be three beats within one second. If there has been only one beat the other values are zero. The reported HR includes Ultra Low Frequency (ULF), Very Low Frequency (VLF) and Low Frequency (LF) fluctuations, whereas HRV is using High Frequency tB2B variation (HFHRV) [5]. We get RR from the respiration modulation of SV and tB2B.

One can of course also generate HFHRV and LFHRV by post-processing the raw beat-to-beat times. ST, extrapolated from FFT_I, indicates bed status, "0" being empty bed, "1" being bed occupied and "2" being movement.

One can filter the reported raw output parameters to analyse e.g. sleep quality and over-night recovery, or to find trends or abnormalities, like indication of sleep apnoea or arrhythmia.

Performance of Sensor

The resolution of the sensor and the external noise from the environment determine the accuracy of the measurement of tB2B and SV. The resolution of the accelerometer is about 40µg in the relevant frequency band and a very steep filter in the BCG sensor removes high frequency vibration.

We first performed a small-scale test on the performance of the BCG sensor using three beds with very different features, one standard hospital bed, one wooden bed (IKEA Sultan Luröy) with a thin mattress and one bed (IKEA Sultan Slåstad) with very soft resonating springs. The vibration damping time constant for an occupied bed ranged from about 0.1 (wooden bed) to more than two seconds (bed with soft resonating springs).

In a second phase, we performed three clinical tests, two in the Turku University Sleep Research Centre [8] and one with the Finnish Institute of Occupational Health [9].

Heart Rate Test

We had ten different test persons (7 male, 3 female) with the age, weight and height in the ranges of 22...59 years, 48...105 kg and 152...197 cm respectively, all tested in the above three different beds.

In 90% of these 30 tests (10 persons x 3 beds) the deviation of the heart rate from that measured with a clinically approved 3-point reference ECG sensor (Mega Electronics, Figure 2) was all the time within ±2 beats per minute (BPM). In the residual 10% of the tests, the reading deviation was within the same ±2 BPM during 95% of the time and within ±5 BPM during the entire test.

Figure 2: Mega Electronics ECG Sensor

Heart Rate Variability Test

We performed a heart rate variability performance test for the BCG sensor with the same bed and ECG reference sensor set up as above. The length of the test sessions was 5…10 minutes, and we had a subset of five test persons (age 22…58 years, height 160…190 cm, weight 50…75 kg).

As the ratio between High and Low Frequency Heart Rate Variability (HFHRV/LFHRV) is the widely accepted standard measure of stress and recovery [6, 7] we used this ratio to evaluate the results of the performance test. In some of the short recordings, the person moving or talking influenced the results. By selecting the recordings with relevant BCG signal for more than 80% of the time (this is a reasonable assumption for overnight recordings) we get a correlation between BCG and reference ECG better than 96% (**Figure 3**).

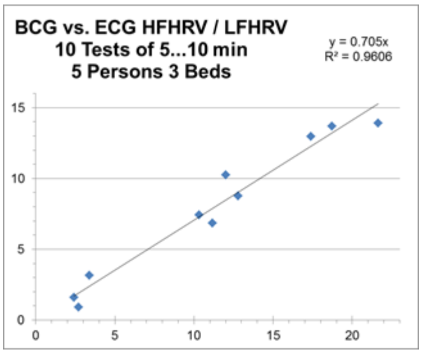
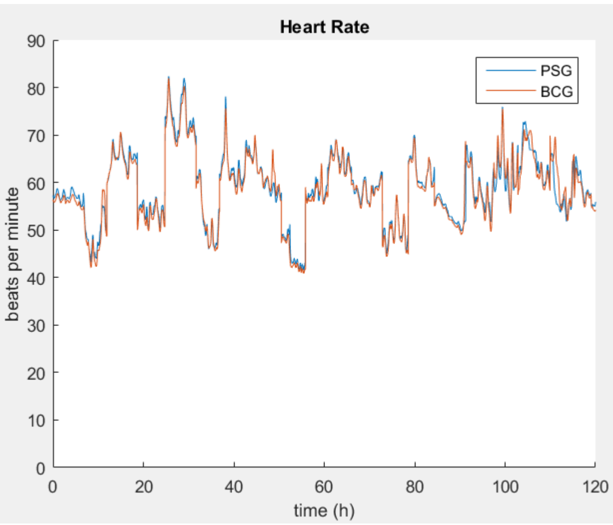


Figure 3: Correlation between HRV ratio of BCG and ECG

Clinical Test in Sleeping Laboratory

We performed two clinical studies (20 persons & 10 persons) at Turku University Sleep Research Centre [8], comparing BCG with Polysomnography (PSG) in overnight sleep analysis. In PSG, the accepted golden standard for sleep analysis, an ECG chest belt measures the heartbeats.

For HR the measured overnight difference between BCG and PSG was -0.5 +/- 3.2 BPM (Ave +/- 2xStd) and the correlation (**R^2**) 97% for 30 min averages [10]. The correlations for HFHRV and LFHRV were 67% and 71% respectively.



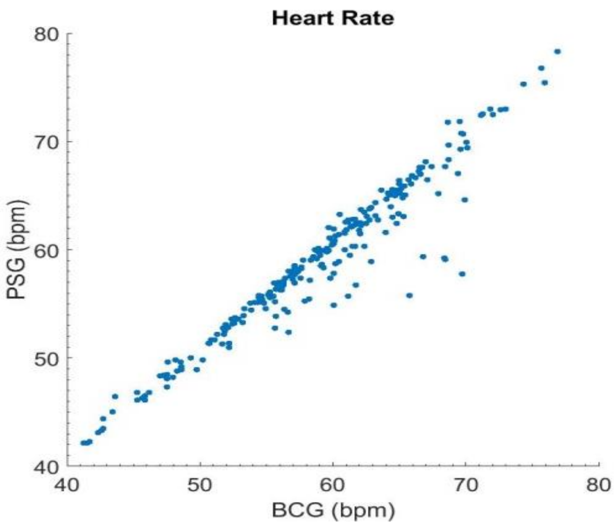


Figure 4: Overnight heart rate and correlation – BCG vs. ECG

Clinical Home Sleeping Test

In a third clinical test, with PSG as reference 16 persons recorded their heartbeats at home, one night each. The difference in HR was -0.5 +/- 5.0 BPM (Ave +/- 2xStd), as well as $\mathbf{R^2}$ for HR 97% and HFHRV/LFHRV 78% respectively, when taken second by second. Figure 5 shows the correlation results. Here vertical outliers are probably caused by the ECG reference, whereas horizontal ones by BCG.

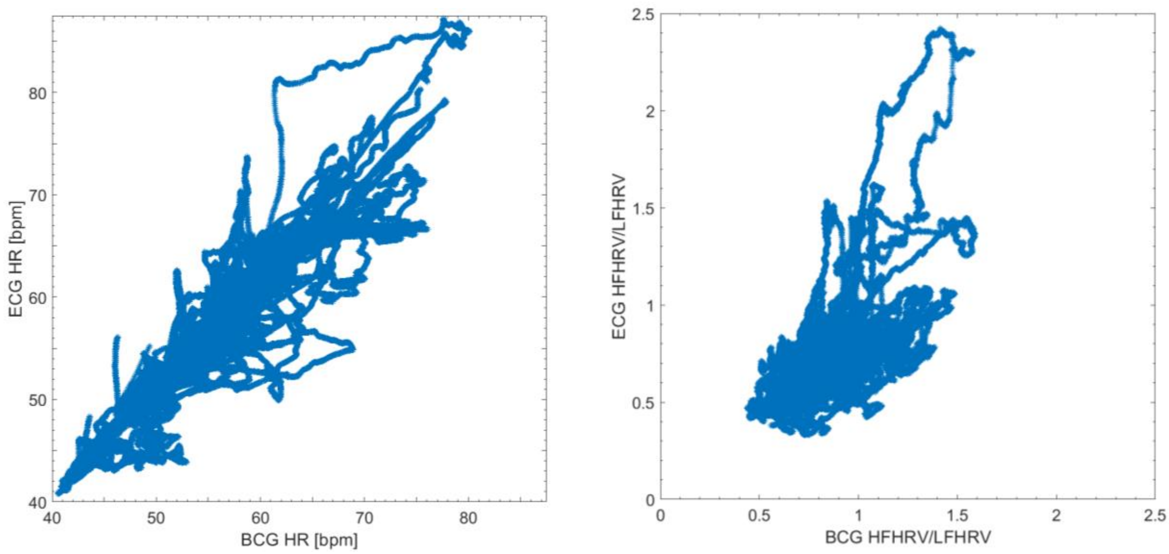


Figure 5: Overnight HR and HFHRV/LFHRV correlation

Filtering and Analysing Overnight Data

With an intelligent filter, we separate false detected beats caused by motion from real heartbeats. In addition, we separate normal heartbeats from those related to pathological arrhythmia. Motion itself is useful information, in addition to the normal heartbeats, for determining sleep status. You can correlate the existence and frequency of abnormal heartbeats to time and sleep stage during the night. Figure 6 shows nocturnal bradycardia with some of the beat-to-beat intervals significantly longer than the rest. Here we can see a Poincaré or Lorentz plot, with the nth tB2B plotted against the following one. The side bands indicate arrhythmia, in this case bradycardia, and the width relative the length of the main distribution the stress – relaxation status of the person, the wider the distribution relative to the length the more relaxed.

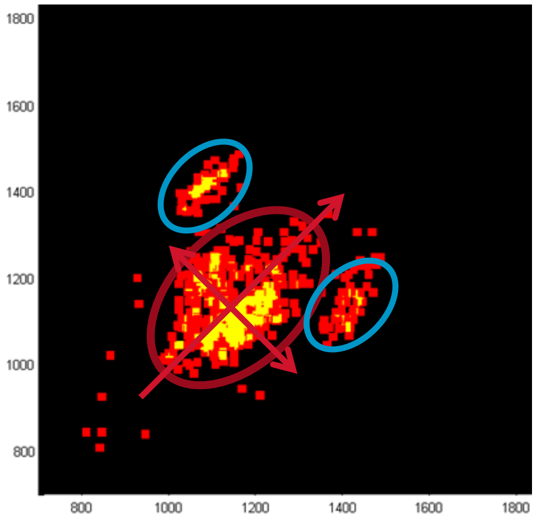


Figure 6: Lorentz plot with bradycardic arrhythmia

SV gives information on respiration depth and frequency, but also on the position of the person in the bed. When turning away from or towards the sensor there is motion and a jump in the average SV. This can be used e.g. for analysing sleep quality or the risk for pressure ulcer in elderly. **Figure 7** shows a restless night, where the person has turned about 15 times and had a very short deep sleep.

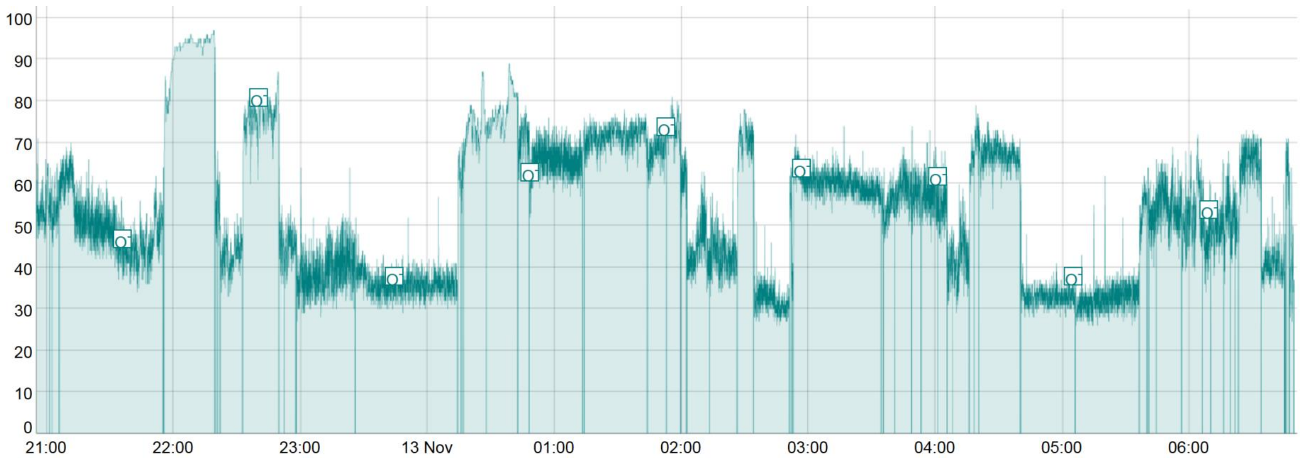


Figure 7: Nocturnal Stroke Volume with 15 clear turns

Sleep apnoea results in characteristic HR oscillations in the VLF frequency band 0.01…0.04Hz (**Figure 8**). One can combine them with corresponding SVV oscillations for good apnoea detection [**12**].

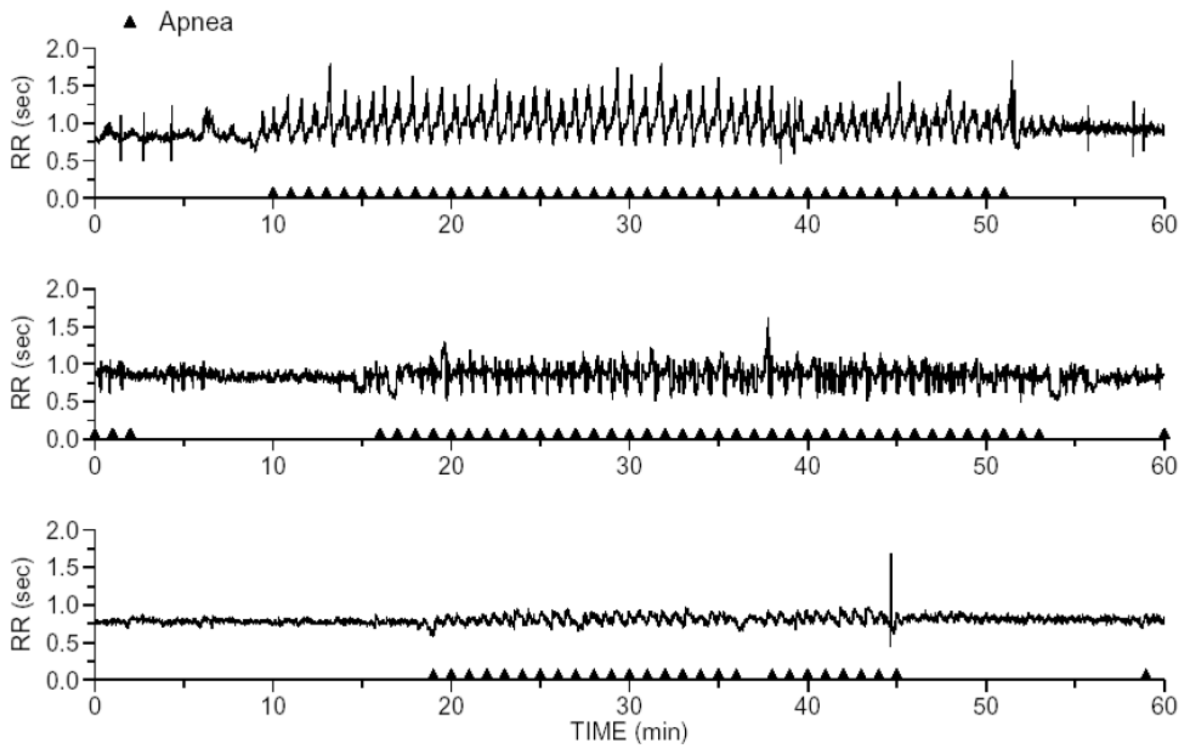


Figure 8: tB2B oscillations during sleep apnoea [14]

Recovery Analysis

Stress and recovery determine sympathetic (sympathetic nerve activating SinoAtrial (SA) and AtrioVentricular (AV) nodes, increasing cardiac output) and parasympathetic reactions (Vagus nerve decreasing cardiac output), which have different behaviours both in time and frequency domain [11]. There are several time domain standard measures and a graphical method (**Figure 6**) to determine the stress/recovery balance, but you can also perform the analysis in the frequency domain.

In our clinical tests we have seen, that the best indicator of parasympathetic reactions and a relaxed state is HFHRV. It indicates both drop of cardiac output and rapid responses to needed increase in cardiac output. We can overcome the usual limitation of the dependence of HFHRV on respiration depth (respiratory sinus arrhythmia), by compensation with the independently extrapolated SV modulation depth (SVV).

On the other hand, the best indication of sympathetic reactions and stress is the increase in HR and slow HR variations. Combining these with the opposite indicators above, we get numbers describing the balance between stress and recovery, which we for simplicity call HRV. During a good night, HRV is cyclic, going up and down, and with an average upwards trend, indicating recovery.

Murata's recovery analysis reports both the relative maximum increase in strongly filtered HRV (R Index), Recovery and its absolute value Relaxation (**Figure 9**).

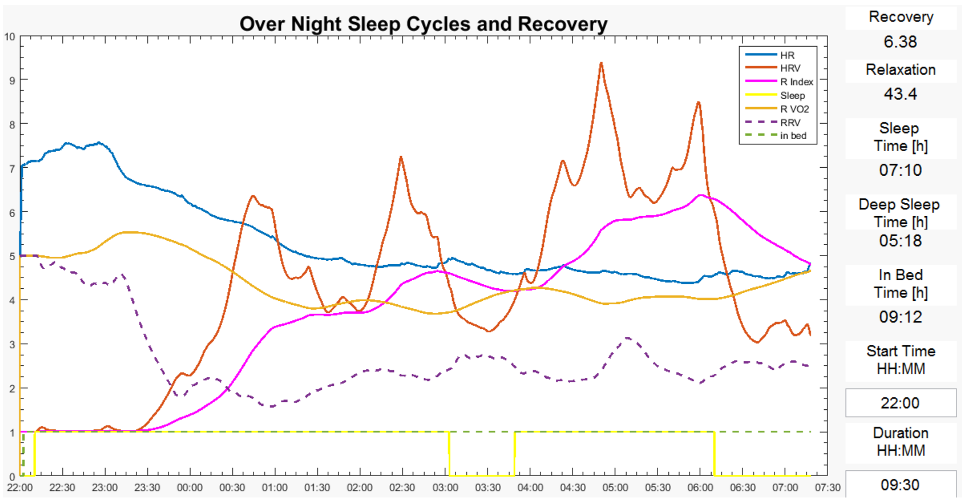


Figure 9: Example of filtered overnight data from home bed

Sleep Analysis

In the different sleep phases, we can observe different reactions in heart activity and respiration (**Table 1**). In **Figure 9** we can see, that when falling asleep HR goes down by about 10 Beats Per Minute (BPM) and respiration becomes regular, i.e. Respiration Rate Variability (RRV) goes down. After that, HRV starts to go up indicating a transition through Light Sleep to Deep Sleep.

Then HRV and RRV continue in anti-phased cycles, indicating sequences of Deep Sleep, Light Sleep, REM Sleep and Wakefulness. The term REM Sleep comes from the normal way of detecting it in PSG, measurement of Rapid Eye Movement. This phase is when you see most of your dreams and it is important for mental recovery, whereas Deep Sleep is important for physical recovery.

Figure 9 also shows an indication of relative oxygen consumption (R VO2), proportional to RR * SVV.

	Light Sleep	Deep Sleep	REM Sleep	Wakefulness
HR	Decreased	Decreased	Increased	Increased
HRV	Medium	Increased	Decreased	Decreased
RR	Medium	Medium	Medium	Medium
RRV	Medium	Low	Increased	High
Rdepth	Medium	Decreased	Increased	Increased

Table 1: Sleep reactions [10]

For the determination of sleep phase we combine all these sleep reactions with motion measurement (status). Hereby we use neural networks for machine learning.

Sleep Cycle Accuracy Consideration

In the clinical tests at Turku University Sleep Research Centre and the home tests, one of the main targets was to clarify the accuracy and reliability of sleep stage indications measured with BCG.

Table 2 shows the cumulative results from the 31 first over-night tests, whereas we in **Figures 10a…10c** can see the corresponding correlation graphs. As sleep determination with PSG is a manual process, based on the gathered over-night data, and performed by a medical doctor or a sleep technician, we wanted to check the variation of this reference measurement as well. Therefore, we had three different sleep technicians analyse the same PSG data. Their variation we can see as the dotted lines in **Figures 10a…10c**.

	Total Sleep Time	REM Sleep	Deep Sleep
Sleep Duration (PSG)	383 $^{+125}_{-245}$ min	65 $^{+65}_{-51}$ min	111 $^{+94}_{-111}$ min
Difference PSG vs BCG (95% estimate)	± 42 min	± 23 min	± 44 min
Median(|Difference|)	2.8 min	3.7 min	9.2 min

Table 2: Cumulative difference BCG vs. PSG

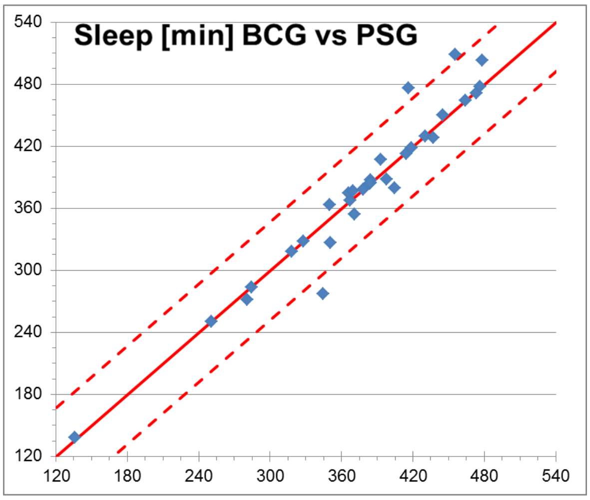


Figure 10a: Correlation graph BCG vs PSG for cumulative sleep

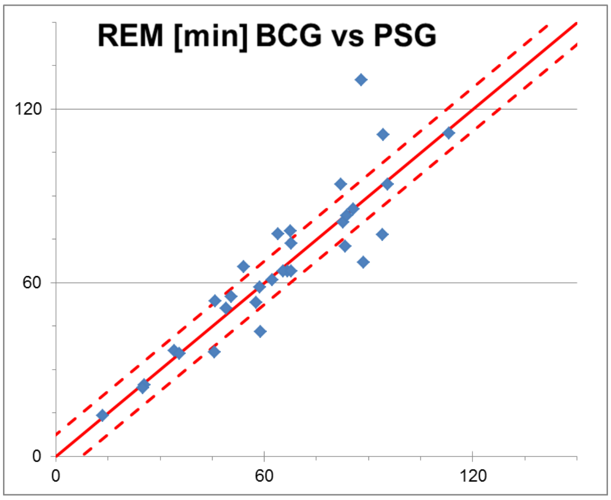


Figure 10b: Correlation graph BCG vs PSG for REM Sleep

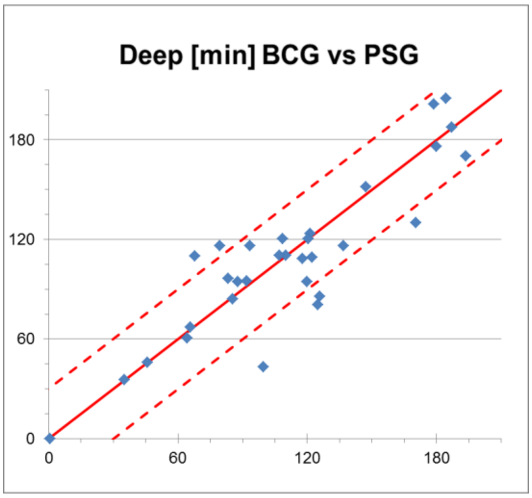


Figure 10c: Correlation graph BCG vs PSG for Deep Sleep

In **Figure 11** we can see the age distribution of the 31 persons tested over-night, 23 males and 8 females.

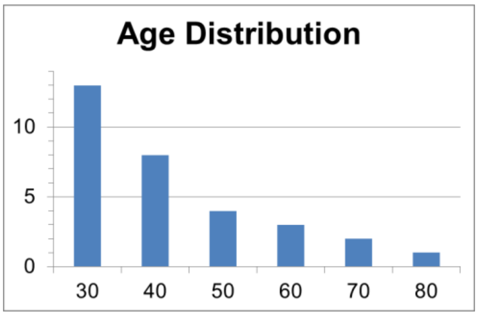


Figure 11: Age distribution of 31 tested individuals

When looking at the sleep phase correlation, epoch-by-epoch (30s), the situation gets a little bit more complicated. For young people and well-trained athletes, with strong sympathetic and parasympathetic reactions, like in **Figure 9**, the correlation is good, typically about 80% for the individual sleep phases and close to 100% for sleep. However, elderly people have weaker and in many cases delayed reactions, making synchronization more difficult. Here the smoothing function in the sleep and recovery also causes a delay, with non-synchronous epoch-by-epoch reactions as a result, when the original reactions are weak. As a result, for some individuals the correlation for the different sleep phases can even be below 30% and for sleep as low as 80%. Normally this should not be a problem, unless you use the measured sleep state for waking up the person.

Conclusions

We see that one can use Ballistocardiography (BCG) for different purposes with a variety of people. In elderly care and for independent living, nocturnal recovery is important, and presence in the bed is likewise valuable information. In these applications, you can combine the data deduced from BCG with other information, e.g. to detect change in behaviour, implying that something is wrong.

Good sleep is important for the prevention of many diseases and for your life expectancy. BCG provides means to perform non-intrusive long term monitoring of sleep quality. BCG can help athletes and active exercisers control their recovery, avoiding acute and chronic over-training.

In today's hectic world, sleep problems, resulting in increased physical and mental stress with e.g. decreased performance at work as a result, are very common. Hereby BCG based sleep monitoring can help detecting and controlling the problems.

Finally, continuous nocturnal monitoring may discover pathological conditions, such as sleep apnoea, arrhythmia and of course, conditions like infections, which one can see as increased stress.

Murata's Products

Murata offers a reference design, including an accelerometer and a pre-programmed micro-controller for the BCG measurement. With the support material available, integration of the BCG measurement can be done in a variety of applications.

In addition, the Murata Sleep and Recovery Analysis software library is available for post-processing the BCG output data into meaningful sleep analysis metrics. The output data can be used as such, or to make further analysis, e.g. regarding sleep or pathological conditions.

There is a number of granted patents [12] and patents pending covering Murata's BCG related products.

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