Reliability of telemedical Heart Rate meters

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In this paper we analyze low-cost commercial chest belt for integration into a lifestyle counselling system as a source of heart rate data. We compared data from a Schiller ECG Holter device which served as gold standard device with a CardioSport device. Because of missing data in the CardioSport device caused by losing contact with body, creation of special algorithms was necessary for synchronization and filtering. The results show that using our synchronization algorithm the average mean absolute percentage error between the two signals was 2,32% with correlation of more than 99%. With the filtering algorithm, we were able to get more than 70% of the signal on average with an absolute percentage error of 2,62% and a high average correlation of 98,76%. The mean RR interval values and standard deviation of RR intervals are very close to the gold standard device using both the synchronization and filtering algorithm. With filtering, the gold standard measurements produced only slightly better results related to false detections of atrial fibrillation than the CardioSport device. In conclusion we can state that with a simple pre-processing algorithms, CardioSport as a low cost device, can be safely integrated into a lifestyle support system in a telemedical solution.

INTRODUCTION

Low cost telemedical sensors are often used in modern ambient assisted living (AAL) telemonitoring and self-management systems to provide input for medical intelligence algorithms [1,2,3]. Such systems extend the horizons of traditional health care based purely on point of care measurement data, but the proper interpretation and reliability of the results depend on the reliability of the measured data and the sensor itself. Nevertheless, there are still surprisingly few reviews reported in the literature to date on the validation of the information content of such low cost sensors compared to a clinically accepted “gold standard” device. We could find several devices that were tested for validity like SenseWear HR Armband[4], Smarthealth Watch [5], Actiheart [6,7], EquivitalLifeMonitor [8] and Bioharness™ Multivariable Monitoring Device from Zephyr that has been tested for validity [9,11] and reliability [10,11]. All of them used gold standard device simultaneously with tested device as a methods for validating data. However, most of the compared devices are high-end devices with considerable price which present an obstacle for the penetration of telemedicine.

In this proof-of-concept paper, we analyze a simple commercial chest belt chosen for integration in the Lavinia lifestyle mirror system [12] as a source of heart rate (HR) data. In Lavinia, the HR signal of the patient will be used

- to estimate the calories burnt by physical activity,
- to calculate the heart rate variability (HRV) in order to detect periods of mental or emotional stress, and also
- to analyze arrhythmia patterns (Poincaré plots) for atrial fibrillation detection

Therefore, our approach will involve the comparison of the HRV and Poincaré plots computed from the filtered chest belt signal, to those parameters computed from a “gold standard” Holter device.

METHODS

Measurement procedure

In order to make the measurements, the two devices were used simultaneously by a healthy volunteer during 24 hour long period. A Schiller MT-101/MT-200 Holter device was our reference device (Figure 1), designed for clinical use and we treated results from this device as gold standard.

Figure 1
Schiller MT-101/MT-200

The chest belt was a CardioSport TP3 Heart Rate Transmitter device. Since this device does not have its own memory for storing data, we used a Nexus 7 tablet with Android version 4.4.2 to connect to the device with the Bluetooth 4.0 protocol and store the measured data on the tablet.

Figure 2
CardioSport TP3 Heart Rate Transmitter

Although both devices were worn by the volunteer for 24 hours, only 12 hours of the overall signal has been used for analysis because the nighttime chest belt measurements were useless due to the frequent detachment of the device from the body. We could improve results during nighttime using tapes for fixing the device closely to the body but since we wanted to test the device for telemedical purposes, we could not expect users to apply the tape all the time during everyday activities.

Because nighttime data were unusable, we reduced time of the measurement to 12 hours and repeated the measurement on 4 more healthy male subjects.

SIGNAL ANALYSIS

The direct comparison of measured data was impossible due to the different design of the gold standard and the telemedical devices. However, we wanted to be able to compare signals directly in the time domain and also to develop an algorithm for filtering out the noisy parts of the CardioSport device measurements reliably without using the gold standard data. The problem is that the chest belt is not firmly attached to the body and a quick movement of the device can sometimes cause signal loss (especially during sleep). Therefore, we needed to create a software module for synchronization and filtering before any further analysis. Filtering means to remove obviously bad data (artifacts) and to keep only "good" data segments of sufficient length, because, as a rule of thumb, both HRV and Poincaré plot computation requires data chunks of at least 5 minutes.

THE SYNCHRONIZATION ALGORITHM

Our simple algorithm for signal synchronization uses a sliding window that passes from the beginning of the chest belt signal to the end and calculates the absolute error between the two signals. When sliding is over, the location of the sliding window with the minimum absolute error is considered as the point where the two signals should be synchronized. This applies only if the correlation of the data in the sliding window and the same amount of data from the gold standard is higher than a minimum set by the user. If these conditions are met, the algorithm copies data from the sliding window into a newly generated third signal which represents the chest belt signal fully synchronized with the gold standard signal. If conditions are not met, the third signal is filled with zeros. At the end, the algorithm extracts all the highly correlated segments from the third signal skipping zero values. Also, a file with all the merged segments is generated for general analysis. The algorithm uses the following 5 main parameters that can be set up by user:

- Window size – how much data is copied from the signal into the sliding window (default: 200),
- Window shift step – number of samples by which we shift the sliding window in each iteration (default: 50),
- Absolute error window – how much data will be used to calculate the minimum absolute error (default: 200),
- Maximum error distance – number of samples by which we shift the absolute error window in order to find the minimum absolute error (default: 1000),
- Minimum correlation –minimum correlation, expressed as a percentage, required for the two signals to consider data in the chest belt signal accurate (default: 97%).

Each parameter has its own default value, shown in parentheses, which was determined empirically. After running the synchronization process, we got segments of highly correlated data. Figure 3 shows how the lengths of signal segments are distributed. We can see that most segments are 3 -18 minutes long. The longest segment highly correlated with the gold standard data is 110 minutes long. The default parameter settings minimize the number of overly short (< 5 min) segments. Most of the bad segments (Figure 4) are shorter than one minute, and only one bad segment was 60

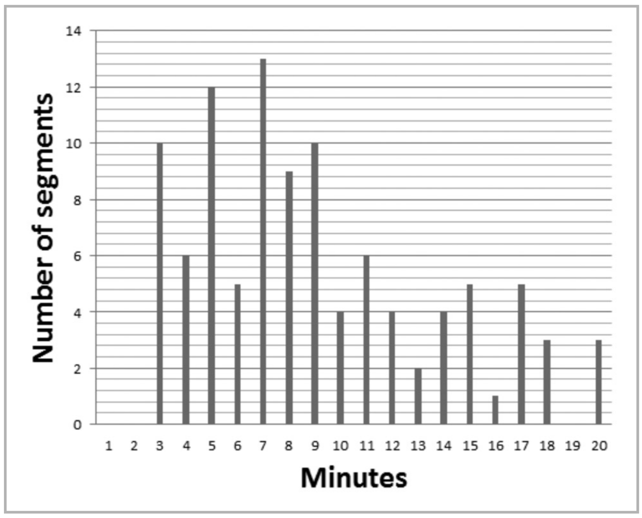

Figure 3
Distribution of highly correlated segment lengths for all subjects

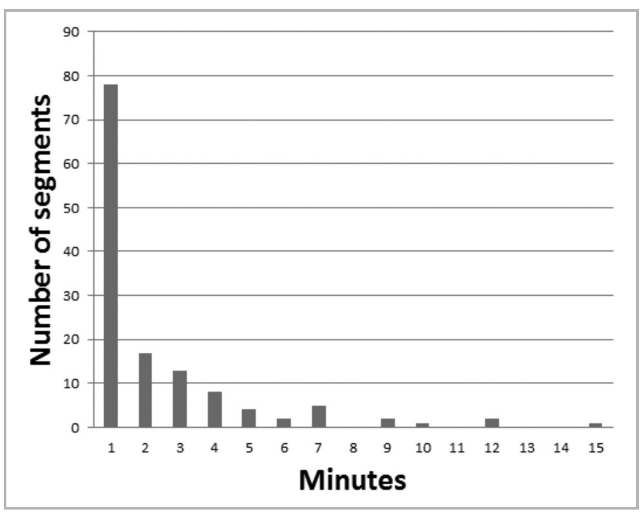

Figure 4
Distribution of low correlated segment lengths for all subjects

minutes long. We excluded one subject from calculations due to low quality of results, probably due to the incorrect placement of the gold standard electrodes.

THE FILTERING ALGORITHM

The second part of the algorithm is used in the real telemedical scenario, for finding good parts of the signal without the gold standard data. This means finding gaps and abnormal values and skipping them. First, we compare the timestamp of each data item with the timestamp of the previous one. If the difference between the timestamps is bigger than 3 seconds, we mark this data as a gap. 3 seconds is used for gap detection because the chest belt has a buffering system that can tolerate short detachments of the device from the body. If more than 3 seconds is used, some data could be missing which could cause errors in further data analysis. In the second step we identify abnormal values in the signal. It is important to emphasize that we do not modify data in any way as we do not want to influence measurement data which could potentially give us false results in analysis. Instead, abnormal values are treated the same way as gaps. The abnormal values are identified by observing the mean value of 20 neighborhood samples (10 previous and 10 following ones). If this mean value differs from the value of the current sample by more than 300, we consider it invalid and marked as gap/error in the signal. Finally we extract the good segments from the signal with a length of more than 5 minutes.

We implemented the above algorithms in a simple software tool (Figure 5).

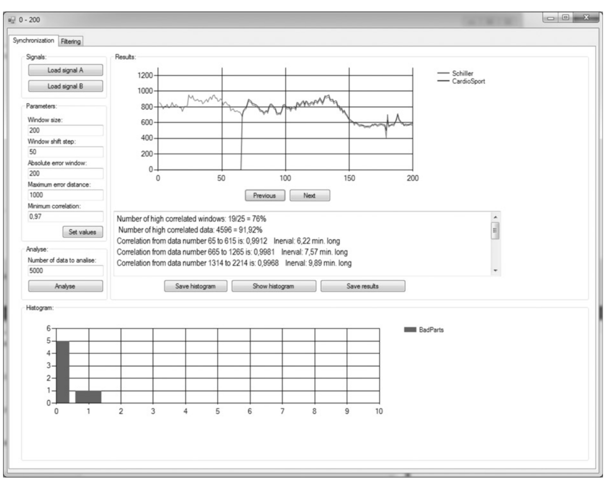

Figure 5
Synchronization and filtering software

STATISTICAL ANALYSIS

Analysis was made for data produced by synchronization and filtering algorithms on HRV and atrial fibrillation. Time domain analysis, correlation comparison, mean absolute percentage error and the slope of scatter plot diagram was compared between two measurements for HRV analysis, while the specificities of a self-developed atrial fibrillation detector algorithm – based on the k-means clustering of Poincaré plots (consisting of RR intervals) [15] – related to the two measurements were compared for atrial fibrillation analysis.

The time domain analysis for HRV was performed in Kubios HRV analysis software [13], while the rest of the analysis for HRV and atrial fibrillation was performed in Microsoft Excel. The atrial fibrillation detection was done in MATLAB environment and the results were saved as Microsoft Excel workbooks.

RESULTS

HRV

Synchronization

After synchronization procedure we got highly correlated (greater than 97%) synchronized data with various duration. Table 1 shows overall duration of signals. Subject #1 had the lowest usable time with only 2 hour and 6 minutes. Probable reason for such a low time is chest hair which reduced the contact between electrodes and the skin. Because of such short duration, this subject was excluded from calculation of average results.

Subject number	Duration (h:m:s)
#1	2:06:18
#2	10:53:28
#3	8:45:40
#4	10:30:17
#5	7:46:56

Table 1
Signal duration after synchronization process

Table 2 shows results in time domain for Schiller and CardioSport devices after using algorithm for synchronization of signals. Time domain analysis shows pretty close values for both, mean RR values and standard deviation (STD RR, see on Figure 6). Average Mean RR values for Schiller and CardioSport devices are 850,80 and 870,69 respectively. Average STD RR for Schiller device is 108,42 and 110,93 for CardioSport device.

$$STD\ RR = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(RR_j - \overline{RR}\right)^2}$$

Figure 6
Formula for standard deviation of RR intervals

Figure 7 represents relationship between CardioSport and Schiller device on all five subjects using scatter plot. It can be seen that lowest slope value is 0,9683 while the highest value is 0,9791. Average mean absolute percentage error (MAPE) between two signals is 2,32% with an high average correlation of 99,67%.

	Mean RR (ms)		STD RR (ms)	
Subject number	Schiller	CardioSport	Schiller	CardioSport
#1	738,27	755,47	123,34	125,09
#2	704,04	720,42	91,35	93,47
#3	907,63	928,88	90,40	92,83
#4	854,53	874,50	144,74	148,00
#5	937,01	958,97	107,18	109,41
Average	850,80	870,69	108,42	110,93

Table 2
Time-Domain Results after synchronization process

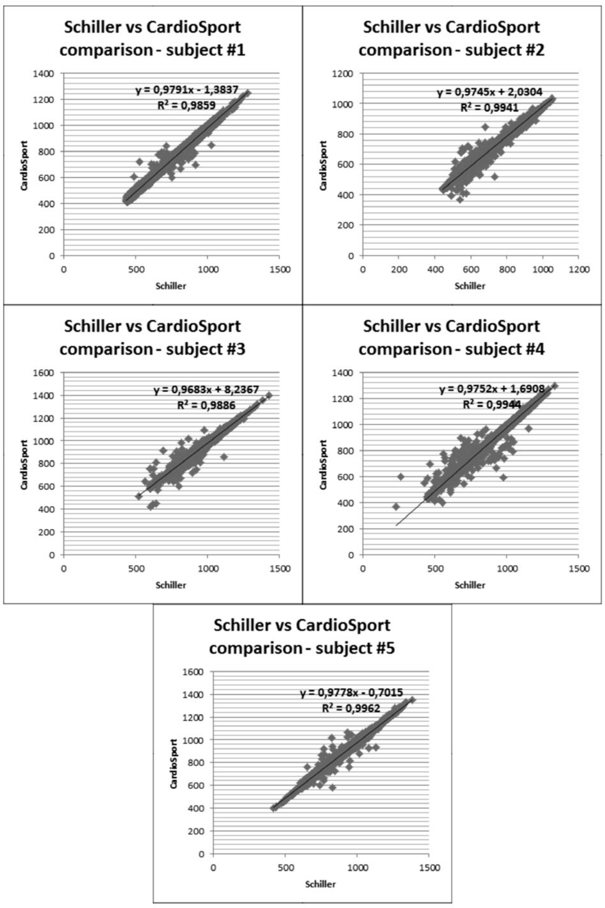

Figure 7
Scatter plot representing relationship of CardioSport and Schiller devices after synchronization process for all 5 subjects

FILTERING

Using filtering algorithm, we extracted values from the signal. Duration of the resulting signal is shown in table 3. As in synchronization process, we also got very short duration for one subject and we discard this subject in calculation of average values. It is important to note that due to the noise on Schiller device records, we had to remove noisy parts from original signal. Therefore, even though signal was recorded 12 hours continuously, overall duration is much less. Calculation shows, that in worst scenario, only 45% of signal can be used for analysis using this filtering method. However, in best scenario this number reaches 95%. This leads to conclusion that results are very much subject dependent.

Subject number	Duration (h:m:s)
#1	1:28:10
#2	11:20:03
#3	6:15:38
#4	9:27:07
#5	4:29:44

Table 3
Signal duration after filtering process

Results of data analysis in time domain after filtering out the bad parts can be seen on Table 4. We can see that mean RR intervals for Schiller and CardioSport devices are 851,14 and 871,23 and standard deviations are 104,61 and 106,35 respectively. CardioSport device has slightly greater values but they are very close.

	Mean RR (ms)		STD RR (ms)	
Subject number	Schiller	CardioSport	Schiller	CardioSport
#1	707,80	724,03	136,04	138,63
#2	700,40	716,70	91,33	93,24
#3	899,20	920,97	99,67	99,77
#4	846,46	866,25	139,26	142,33
#5	958,49	981,00	88,16	90,08
Average	851,14	871,23	104,61	106,35

Table 4
Time-domain analysis after filtering process

Minimum, maximum and average percentage error on whole signal was calculated using 5 minute long sliding window with one minute shift step (Table 5). Only one subject has very high maximum error value of 33,86%. By visual examination, it is determined that the cause of such high error was in Schiller device artifacts. Despite that, average error values are at very low level of 2,20%.

Subject number	Minimum error	Maximum error	Average error
#1	0,08%	3,50%	1,50%
#2	0,01%	7,71%	2,12%
#3	0,04%	33,86%	3,22%
#4	0,13%	6,72%	1,92%
#5	0,07%	5,11%	2,22%
Average	0,06%	13,35%	2,37%

Table 5
Minimum, maximum and average percentage error

Figure 8 represents relationship between CardioSport and Schiller device on all five subjects using scatter plot. All slope values are close to 1. Lowest slope value is 0,9757 while the highest value is 1,0184. Average mean absolute percentage error (MAPE) between two signals was 2,62% with an high average correlation of 98,76%.

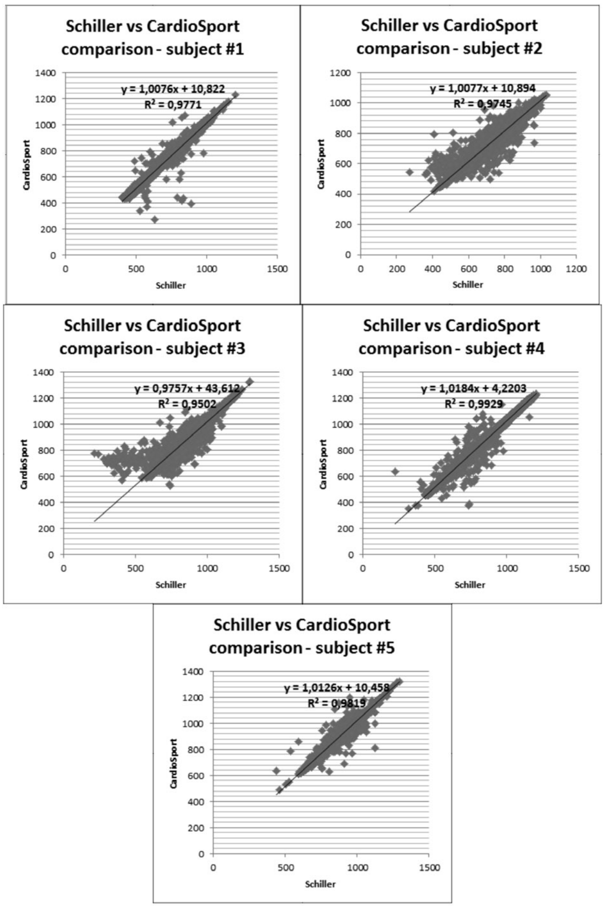

Figure 8
Comparison of CardioSport and Schiller device after filtering for all 5 subjects

ATRIAL FIBRILLATION

We performed the atrial fibrillation (AFib) detection by analyzing Poincaré plots consisting of 30 RR intervals. We considered 30 RR intervals per iteration and did the following in each iteration after constructing the Poincaré plot. We calculated the dispersion around the diagonal line and used k-means based cluster analysis to determine the number of the clusters. If the dispersion was too high (> 0.06) and the number of clusters was 1, or the number of clusters was more than 9; we signed that series of RR intervals as “AFib”, else we signed it as “Non-AFib”. The details of the algorithm can be seen in our previous study [16].

Since our data set did not contain real AFib cases, only specificity could be calculated related to the efficiency of the detection.

SYNCHRONIZATION

The evaluation of atrial fibrillation detection results for the synchronized measurements can be seen in Table 6.

Patient	Number of iterations [#]	Schiller MT-101/MT-200 system				CardioSport TP3 Heart Rate Transmitter			
		AFib cases		Non-Afib cases		AFib cases		Non-Afib cases	
		[#]	[%]	[#]	[%]	[#]	[%]	[#]	[%]
B. G.	1120	7	0.63	1113	99.38	5	0.45	1115	99.55
F. K.	1796	9	0.50	1787	99.50	3	0.17	1793	99.83
I. K.	1427	11	0.77	1416	99.23	16	1.12	1411	98.88
B. P.	331	26	7.85	305	92.15	31	9.37	300	90.63
I. V.	964	46	4.77	918	95.23	45	4.67	919	95.33
Min	-	-	0.50	-	92.15	-	0.17	-	90.63
Max	-	-	7.85	-	99.50	-	9.37	-	99.83
Mean	-	-	2.90	-	97.10	-	3.15	-	96.85
STD	-	-	3.30	-	3.30	-	3.91	-	3.91

Table 6
Result table of the synchronized data related to atrial fibrillation detection. Values in the 6th and 10th columns denote the specificities of the Schiller and CardioSport data respectively.

FILTERING

Table 7 represents the results of the atrial fibrillation detection related to the filtered signals.

Patient	Number of iterations [#]	Schiller MT-101/MT-200 system				CardioSport TP3 Heart Rate Transmitter			
		AFib cases		Non-Afib cases		AFib cases		Non-Afib cases	
		[#]	[%]	[#]	[%]	[#]	[%]	[#]	[%]
B. G.	808	15	1.86	793	98.14	3	0.37	805	99.63
F. K.	1879	29	1.54	1850	98.46	2	0.11	1877	99.89
I. K.	1296	10	0.77	1286	99.23	20	1.54	1276	98.46
B. P.	241	3	1.24	238	98.76	8	3.32	233	96.68
I. V.	544	6	1.10	538	98.90	7	1.29	537	98.71
Min	-	-	0.77	-	98.14	-	0.11	-	96.68
Max	-	-	1.86	-	99.23	-	3.32	-	99.89
Mean	-	-	1.30	-	98.70	-	1.33	-	98.67
STD	-	-	0.42	-	0.42	-	1.27	-	1.27

Table 7
Result table of the filtered data related to atrial fibrillation detection. Values in the 6th and 10th columns denote the specificities of the Schiller and CardioSport data respectively.

DISCUSSION

We compared the results using standard deviation, correlation and scatter plot diagram with slope of the regression line which are commonly used in literature [6,9,14]. However, before we analyzed the results we performed filtering with simple algorithm to eliminate noisy parts without using any data for comparing with gold standard device. Such method reduces the overall time of the signal but it increases quality of signal. After filtering, all the results of CardioSport device are very close to Schiller device with average correlation of 98,73%.

According to the results of the atrial fibrillation detection we can say that the specificity of the algorithm is good enough compared to other similar methods in the literature [15, 16, 17]. Without using golden standard signal we obtained minimum and mean specificities of 96.68% and 98.67% respectively (see Table 2), which means that the number of false positive values is relatively small. Surprisingly, the first two rows of Table 2 indicate that CardioSport outperforms the Schiller device in that cases related to false detections.

CONCLUSION

Even though the CardioSport device, due to its design, may suffer from signal loss, we managed to determine that it can be safely used for telemedical purposes of measuring HRV and atrial fibrillation. We found only few usable data segments that were less than 5 minutes long and with our algorithm detecting gaps and errors in signal and filtering them out with average effectiveness of more than 70%, we can be sure that during daytime we will have enough data for calculating HRV and atrial fibrillation.

About atrial fibrillation detection we can conclude that, by using the developed filtering algorithm, our golden standard of Schiller MT-101/MT-200 measurements produced only slightly better results related to false detections than the CardioSport TP3 Heart Rate Transmitter. In two cases the CardioSport measurements proved to be even better than Schiller records which imply that some relatively simple heart rate recorders can be the equal of some Holter devices after filtering. We have to emphasize, however, that we have not performed any measurements on atrial fibrillating patients yet. Therefore the investigation of the sensitivity of our atrial fibrillation detection algorithm under the presented circumstances could be subject of further studies.

Our final conclusion is that, with simple pre-processing algorithms, CardioSport as a low cost device can easily be integrated into an lifestyle support system in a telemedical solution.

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