Heart rate analysis with NevroEkg

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Abstract – NevroEkg is a computer application for analysis of ECG and related bio-signals, such as breathing and blood pressure. It was made in collaboration between computer scientists, engineers and neurocardiologists. Recently, it has been modified to also support the unconventional measurements of differential ECG, made on wireless wearable gadgets. These wearable gadgets measure ECG a bit differently - with lower resolution, lower sampling frequency, and more noise. These features require modified and additional processing of the ECG signal, which is not required for standard 12-channel ECGs. A novel algorithm is proposed to help the human operator handle beat-detection in novel ECG measurements.

I. Introduction

NevroEkg is a toolset for computer visualization and analysis of multi-channel ECG and related bio-signal measurements for neurocardiologists [1]. It was implemented in a way that makes analysing short and noise-free measurements that were made in controlled conditions relatively easy and automated. Novel wearable battery-powered gadgets that measure ECG [2] are becoming affordable for health monitoring, and are able to produce so far unseen amounts of ECG data per subject. Wearable gadgets presents a novel means of taking ECG measurements though, which differs from the well-established means in many aspects, and produce different measurements. The main characteristics of ECG measurements produced by wearable gadgets are listed below:

- Measurements are performed in **an uncontrolled environment**, on subjects on their everyday lives, performing their routine tasks or jobs.
- Current technology enables **over 3 days of continuous ECG measuring**. In the future, the continuous measurement time will likely extend for over a week [4].
- Since the measurements are performed on active subjects, they are far **noisier** than the measurements made on resting subjects.
- The wearable gadgets measure **single-channel** ECG, sacrificing the benefits of multi-channel measurements for the benefits of simplicity and unobtrusiveness [5].
- Measuring ECG against the common potential is not possible, since the wearable device only uses two electrodes, therefore **the differential ECG** is measured as the difference between voltage on those two electrodes.
- The aim for long battery life imposes limitations on measurement precision. Relatively **low sampling frequency and low sampling resolution** are usually used on wearable gadgets, compared to modern electrocardiography devices. In this work, gadget that samples ECG with 10 bits and 125 Hz is used.
- Allowing for **lossy data transmission** further lowers power requirements of the wearable gadgets and simplifies their hardware and is therefore justifiable. It is reasoned, that the sheer length of measurement more than compensates for the small number of missing samples.

To accommodate processing of large amount of ECG data with the presented characteristics, new algorithms and processing procedures were required. NevroEkg was modified to accommodate the new requirements and provide some automatic and some semi-automatic processing of the measurements. The semi-automated beat detection was tested and evaluated on the Physionet MIT-BIH Arrhythmia Database [3].

Section II describes the process of handling data and extracting information from them. Subsections A, B and C describe process in more detail. In section III the tests and results of the proposed algorithm are presented. Section IV summarises and concludes the presented work.

II. Algorithms and methods

Processing of measurement data is divided into three steps: an automatic conversion of input measurement files into a file format recognisable by NevroEKG, a semi-automatic detection of heartbeats and a manual analysis of the observed irregularities in heart rhythm. First two steps must take the characteristics of the acquired data into account, to make the input to the last step – the heart rhythm – as error-free as possible for the human operator that is observing it. The first step comprises the analysis of the measurement input file, i.e, the estimation of sampling frequency, the missing data detection, and error detection and handling. This is described in details in subsection IIA

Semi automatic detection helps the human operator to quickly process long measurements containing thousands of beats. This work is normally done manually, and to achieve precise results this is still the preferred method. However for long measurements, where relatively large percentage of beats are regular, a quick method of generalized beat detection is a valuable addition. It is presented in subsection IIB

As the last step, human operator can detect grouped anomalies in the measurement when given an overview of the detected beats. This step still includes human knowledge and intuition. It is important to be done manually, particularly since the subject is mobile during the measurement, and automatic detection could misinterpret the normal changes in the rhythm as an anomaly. We discuss the method of visual analysis in section IIC

A. *Data converter*

The collected data is encapsulated in a simple text file format, as a stream of packets, where each packet comprises timestamp in nanoseconds, sample counter, and sequence of integer-valued samples with constant size. Currently all packets contain exactly 14 samples. Text file also contains meta information, such as the measurement start time, the identifier of the gadget that performed measurement, the sampling frequency, the multiplier and offset for translating sample values, the patient-specific metadata, and user comments. The NevroEKG proprietary nekg file format is able to include all the given meta information, as well as multiple measurement channels, and multiple event channels, which are derived from the measurement channels. Both NevroEKG and its file format are not, however, designed to hold information about the missing data.

The converter processing can be summed up in the following steps:

1. Reading of all contents of the input file into a structured form – separating timestamps, counters, samples, and metadata.
2. Checking for consistency of timestamps and counters, with automated fixing of errors that could occur during the packet transmission. Packets with nonconformant timestamps are discarded while the deviating sample counters with small errors in value (expected value differs by 1 or two) are fixed to match expected values. Missing data is also logged at this step.
3. Sampling frequency is estimated from the counter samples and timestamps by weighted average of the observed sample rates of all continuous sequences (sequences that do not include any missing data). Linear weighting is used that gives each sequence the weight equal to the length of the sequence.
4. Output in nekg file format is written, using the gathered metadata and samples, with the detected missing samples assigned value 0.
5. Problems encountered in the conversion process are also logged as a comment in the nekg file.

B. *Beat detection algorithm*

Algorithm is based on numerous first derivative based QRS detectors [6], and is probably most similar to the simplified QRS detection algorithm by Pan and Tompkins [7]. The algorithm is provided an input signal in a time series, called *signal channel*. The proposed automated part of the beat detection consists of the following steps.

1) *Low-pass filtering*

The signal channel is filtered with a low pass filter, with a user defined cut-off frequency. This filter is implemented with simple triangular convolution vector whose width corresponds to the cut-off frequency. This step removes most of the high-frequency noise emitting from electrical appliances. This step also ensures that the missing data is handled properly, that is, the values that are used to indicate missing data are not used for calculation, and are not smoothed out. On Fig. 1, the input signal processing is shown with the input signal in red and the filtered signal in blue.

2) *Derivation*

Filtered signal is numerically derived. During the derivation, the algorithm again checks for missing data, and ensures that transitions between measured and missing data are not detected as high derivatives. The derivative of missing data is therefore set to zero, since events cannot be detected in such areas. To simplify the algorithm and to ensure that ECGs of all orientations are handled properly, absolute value of the derivative is used for the beat detection. Thus, there is no need for detection of ECG orientation and signal flipping. A sample absolute value of the derivative is shown in green on Fig. 1.

3) *Amplitude analysis*

Possible beat locations are then detected using amplitude analysis algorithm. This algorithm searches for the areas of the derivative higher than a given threshold. Such peaks are very likely the peaks in QRS complex, more exactly on the slopes between R and S waves. The distance between such peaks represents a close approximate to the RRI (beat-by-beat R to R interval) value.

At this stage, all the peaks are declared heartbeats and inserted into a newly created event channel. Event channel contains events as ¡*time, value*¿ pairs. For heartbeat events, *time* is defined as the absolute time since the measurement start, and *value* is defined as the time passed since the previous event (RRI).

Figure 1. Three steps of the algorithm are shown: red is the input signal, blue is the filtered signal, and green is the absolute value of the first derivative.

4) *Extreme events removal*

The last stage of the algorithm prunes the extreme events. Possible erroneously detected beats include peaks from noisy areas, and peaks from P and T waves. Physical limitations limit the heart beat frequency, therefore, to remove peaks that are less likely to correspond to a QRS complex, peaks that are not within margins of normal heart beat frequency are removed. This is done by imposing minimum and maximum thresholds on the value of heartbeat events. Heartbeat events are removed if their RRI is lower than $0.15s$, or higher than $2.5s$. Maximum threshold thus removes the correctly detected heartbeat events, which occur after long intervals of inactivity in the signal, but correctly removes the obviously bad RRI values contained within those heart beat events. Intervals of long inactivity are expected, since they easily arise from simple problems in the measuring procedure and removing a few good heartbeats from the measurement is a good trade-off for removing bad RRI values.

5) Automatic threshold detection

The proposed beat-detection algorithm has only one parameter to tune - the threshold for peak detection from the signal derivative. Since the algorithm is used on very diverse measurements, the threshold should be defined per measurement. To aid the human operator in selecting an appropriate threshold value, the following approach is used.

Process is employing the previously defined steps. Signal is filtered with the low pass filter of 50Hz, and the filter output is derived. Then the program tries to determine the best value of the threshold for the given derived filter output in a loop over a predefined set of candidate values. From experiences gathered by analysing such signals manually, lower bound for candidate values is defined as 1000, and upper as 15500, the values up to 2000 increment by 250, later by 500. For every candidate value, the amplitude analysis and extreme values removal are performed, followed by calculation of statistics. Statistics are gathered from beats: total number of beats, mean heart rate and standard deviation of heart rate.

To accelerate compute times and disregard thresholds that cause the algorithm to find no useful data, computation may stop before reaching the upper bound. When the algorithm detects a very low average heart rate using a certain candidate value for threshold – 15 beats per minute or less – it searches no further, since higher thresholds only further worsen the calculated statistics and higher values are thus deemed invalid by the algorithm itself. The average heart rate is calculated only from the correctly sampled data, with missing samples disregarded.

After the statistics are gathered for all the candidate values in a loop, they are presented to the human operator. A window is shown, with the statistics plotted on two graphs (see Fig. 2 for an example), to help the operator choose the best threshold value. The first graph shows the standard deviation and average heart beat rate, while the second graph shows the number of heart beats detected.

The candidate value, which results in the lowest standard deviation in heart rate if used as the threshold, is offered to the operator as the best candidate (see the vertical lines on the graphs on Fig. 2). After the operator confirms the selection of the threshold value, the detected beats are converted into an event channel, to be displayed underneath the input signal on screen, as seen on Fig. 3.

As can be seen from the added vertical lines on the figure, the detection of beats on the used ECG measurement latched on the slope of Q wave. This is not the same for all the measurements, the detection latches to the point of highest absolute derivative, the point of which is generally within the QRS complex but may vary within it, due to different possible placements of the differential electrodes on the chest.

The automated approach works well for signals, where the subject has normal heart rhythm most of the time, and there is no constant noise of fixed frequency. For such cases, the operator only clicks OK after reviewing the two graphs of statistics.

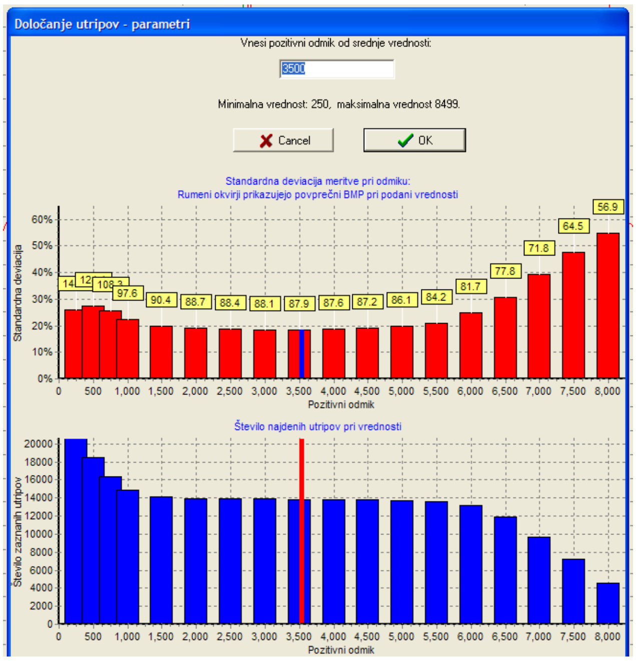

Figure 2. Graph shown to user during beat detection

Figure 3. Result of beat detection.

6) Problems of automatic threshold detection

The operator should visually inspect the graphs, focusing on the threshold values on and near to the proposed candidate value. The standard deviation around the proposed value should be low and heart rate in appropriate bounds, while the number of samples should not change drastically around the proposed value. If these conditions are satisfied, one click on the OK button accepts the threshold and shows the beats on the graph (as seen on Fig. 3). However, some heart beat anomalies can cause the analysis to show multiple areas that satisfy those conditions. Fig. 4 is an example where the analysis returned two areas that seem appropriate for the threshold values. On the Fig. 4, the two mentioned areas are encircled in yellow. This particular analysis occurred on a measurement, where almost every second heart beat was irregular and produced very high peaks in the signal derivative. While the analysis did suggest the value in the proper area in this case, it could also very easily been wrong and suggested a value from the other area. This is why the human operator is included into the algorithm, with the possibility to visually analyse the statistics, to override the suggested threshold and even to repeat the whole beat-detection if the beats are later found to be miss-identified too frequently. The results of the correct threshold selection for this case are shown on Fig. 5.

C. Visual analysis

The presented algorithm is relatively robust, fast, and has good enough accuracy to help the physicians make a basic overview over the collected measurement.

One of the usual methodologies of further ECG analysis is visual inspection of heart rhythm and visualization of problematic sections. Problematic sections are sections of ECG, where rapid change in heart rhythm is seen or a pattern in the heart rhythm changes. An example of whole measurement visualization can be seen on Fig. 6 and of a visualization of a small problematic section on Fig. 7).

Visualisation of the whole measurement provides a global overview of subject's activity and heart rhythm. Several observations can be made from the visual analysis of the measurement overview (Fig. 6).

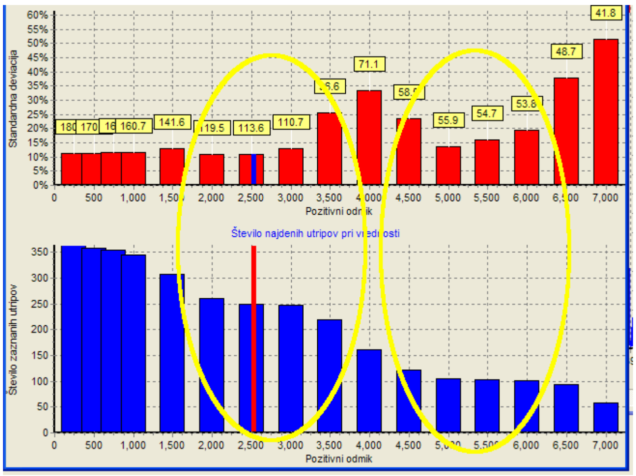

Figure 4. Case of a graph with abnormal heart beat

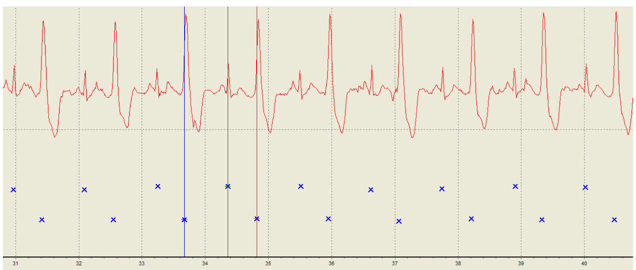

Figure 5. Result of beat detection on abnormal signal

- At the beginning (from 20 to 500 seconds in the measurement), there were no samples gathered. This is an example of gadget losing a connection. During that time there is a flat line in the signal (represented with red line) and no events (blue crosses) are detected.
- Following that period the subject had an unsteady heart rate (area between 500 and 1000 seconds on x axis).
- A steady heart rhythm follows (area between 1000 and 2500 seconds on the x axis). Dispersed events around the relatively steady line indicate irregular heart beats. This is one of the possible indices of problematic areas, allowing the human operator to detect such areas quickly and focus on them.
- On the gathered sample measurement, the subject was involved in a sports activity that periodically raised his heartbeat. This period can be seen quite clearly on the RRI events channel from 3000 seconds to the end of the measurement. Within this periodic activity, there are also numerous outliers in the heart beat events. Those occur mostly in the areas of higher RRI (lower heart rate). Again, these are the areas where the operator should focus on.

Focusing on a smaller area, the signal can be visually inspected in more detail, visualising individual transition in RRI values. Shown on Fig. 7 is a sample of detected transition from irregular to regular heart rhythm. Human operator can inspect such transitions and classify irregularities that are present in the measurement.

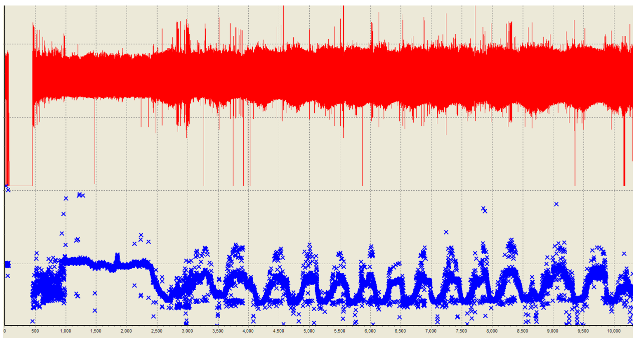

Figure 6. Three hour measurement overview.

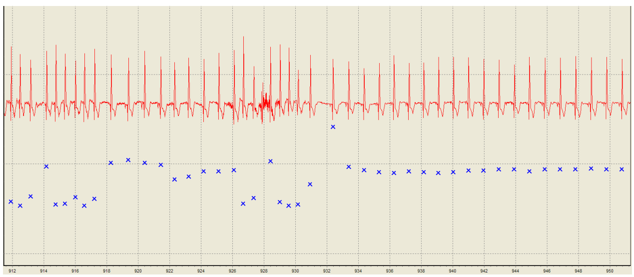

Figure 7. Visual indication of change in heartbeat rhythm.

III. Results

The proposed algorithm was tested on the ECG samples from the PhysioNet's MIT-BIH Arrhythmia Database [3], using MLII channel of each measurement. The detected heart beats were compared to the heart beats annotations from the database. The tests started with the signal being imported into the NevroEkg program where an automatic beat detection was executed (using the threshold value suggested by the algorithm). The resulting RRI event channel was then compared to the beat annotations given by the database. Only the annotations that represent QRS complex were used and all other annotations were disregarded.

The results are presented in Tab. 1, which contains true positive values (tp; correctly detected beats), false positives (fp; falsely detected beats) and false negatives (fn; beats that were not detected). The table are contains the calculated values for precision, defined as $tp/(tp + fp)$, and recall, defined as $tp/(tp + fn)$. The values of precision and recall that are lower than 90% are coloured red in the table.

On the whole database, the execution of the algorithm produced 97.7% precision and 98.9% recall. By design, the presented algorithm always discards the first heartbeat after a long period without detected beats, since its previous heartbeat is not measured and the RRI cannot be determined. Therefore the 100% recall is rarely achievable on arrhythmic measurements. Closer inspection of the table reveals that the variation in results is quite high. There are only three measurements that have precision or recall lower than 95% though, and out of these, the measurement numbered 219 is the worst with precision only 51.2%.

In measurements numbered 108 and 207, the signal to noise ration was the highest. A relatively high threshold was proposed by the algorithm for those two measurements, which helped reduce the number of false positives in beat identification but also caused a lot of false negatives. Precision therefore was high, while recall was low. Measurements 207 also contains periods of ventricular fluttering[8]. Algorithm has not been adapted to cope with such extreme events, and does not distinguish them from noise. In cases with such low recall, the operator should be able to notice the unidentified beats and manually annotate them after a close review of the signal.

To see weather the threshold values could be set more optimally than the one suggested by the algorithm, the measurements numbered 108, 207, and 219 were processed again with human operator in loop. In Tab. 2 the threshold values were manually adjusted until the results were the most satisfactory for the human operator. Detection on measurement numbered 106 shows large improvement, with both precision and recall rising over 90%. Measurement numbered 207, however, includes too many extreme events, such as the previously mentioned ventricular fluttering. Lowering the threshold value manually did improve recall but for the cost of the reduced precision.

In measurement numbered 219, the algorithm with automatically determined threshold latched on both R and the extraordinarily high P waves. Manually setting the threshold lower on this measurement improved precision to 98.3% while recall remained the same, as shown in Tab. 2.

Even without exclusion of record 207, results are comparable to known robust detectors [7, 9, 10], that are also able to detect beats with both precision and recall in 85-99% range.

TABLE 1. RESULTS OF AUTOMATIC BEAT DETECTION ON MIT-BIH ARRHYTHMIA DATABASE

File	tp	fp	fn	Precision [%]	Recall [%]
100	2272	0	1	100.000	99.956
101	1862	5	3	99.732	99.839
102	2180	6	7	99.726	99.680
103	2083	0	1	100.000	99.952
104	2213	37	16	98.356	99.282
105	2551	58	21	97.777	99.184
106	2018	3	9	99.852	99.556
107	2132	3	5	99.859	99.766
108	1227	0	536	100.000	69.597
109	2530	2	2	99.921	99.921
111	2122	0	2	100.000	99.906
112	2538	0	1	100.000	99.961
113	1793	0	2	100.000	99.889
114	1878	4	1	99.787	99.947
115	1953	0	0	100.000	100.000
116	2390	2	22	99.916	99.088
117	1534	0	1	100.000	99.935
118	2277	5	1	99.781	99.956
119	1987	3	0	99.849	100.000
121	1860	3	3	99.839	99.839
122	2475	1	1	99.960	99.960
123	1517	0	1	100.000	99.934
124	1618	0	1	100.000	99.938
200	2596	28	5	98.933	99.808
201	1953	2	10	99.898	99.491
202	2134	1	2	99.953	99.906
203	2921	145	59	95.271	98.020
205	2640	0	16	100.000	99.398
207	2035	51	297	97.555	87.264
208	2917	7	38	99.761	98.714
209	3004	3	1	99.900	99.967
210	2638	24	12	99.098	99.547
212	2747	0	1	100.000	99.964
213	3249	1	2	99.969	99.938
214	2255	5	7	99.779	99.691
215	3362	1	1	99.970	99.970
217	2199	2	9	99.909	99.592
219	2151	2052	3	51.178	99.861
220	2047	0	1	100.000	99.951
221	2427	0	0	100.000	100.000
222	2478	5	5	99.799	99.799
223	2600	0	5	100.000	99.808
228	2028	48	25	97.688	98.782
230	2255	3	1	99.867	99.956
231	1570	0	1	100.000	99.936
232	1701	6	79	99.649	95.562
233	3074	1	5	99.967	99.838
234	2752	0	1	100.000	99.964
$\sum$	108743	2517	1223	97.738	98.888

TABLE 2. TABLE OF RESULTS FROM MIT-BIH ARRHYTHMIA DATABASE, WITH MANUAL THRESHOLD CORRECTION

File	tp	fp	fn	Precision [%]	Recall [%]
108	1654	55	109	96.782	93.817
207	2098	137	234	93.870	89.966
219	2151	37	3	98.309	99.861

IV. CONCLUSION

During the development of the proposed algorithm, input from multiple areas of expertise was considered. Most of the focus was gathered in the area of enabling quick visual analysis of the signal.

The gathered low resolution noisy samples with missing data have been successfully handled with the proposed semi-automatic algorithm. The algorithm and manual work-flow do require some practice for the human operator to perfect, but are easily understood and can be used after a short introduction. Operators have confirmed that such presentation and the proposed algorithm are sufficient for general overview of long measurements.

The goals of reducing human operator workload, and speeding up and simplifying the process were fulfilled, even though further improvements are still possible. There is no standardized method of processing long and noisy ECG measurements yet.

While awaiting further feedback from human operators that are testing the program, some areas of the process are already recognized as improvable. For example, some speed up of the process could be achieved by using parallel processing on the signals. Post-processing of the result would benefit from improved accuracy and could also expand by adding beat classification. Building upon the improved post-processing, the detected problematic areas or individual beats could also be reported to the human operator in a concise manner, accompanied by written explanation.

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