ECG monitoring of cardiac patients at home:

experiences with scenarios and signal processing methods

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Abstract—**Controlled cardiac rehabilitation has shown to be an effective and cost-efficient form of treatment. However, it could be supported by technology. We used a scenario-based method to approach the issue and to consider it from the technical perspective. We also tried out signal processing methods in rejection of artifacts and quantization of ECG features from ECG data collected with two different portable recorders. For example correct R-peak detection rates ranged between 98.2% and 99.9% with 5 different tested R-peak detection routines. Conclusions: comments resulted from the scenario work was educative and simple ECG signal processing results promising.**

Keywords: ECG, signal processing, scenario evaluation, cardiac patient

I. INTRODUCTION

Cardiovascular diseases are the leading cause of death globally and it is estimated to remain in the number one position. Heart attack or stroke caused 76% of these deaths [1]. Evidence shows that controlled (exercise-based) cardiac rehabilitation (CCR) is the most effective method in the treatment of coronary heart disease [2, 3]. Although CCR is effective, it is not used systematically due to lack of resources. For example, only 10-15% of cardiac patients in Finland receive CCR, according to EuroaspireII study [4]. Compared to some other European countries the same figure is close to 50%.

ECG monitoring can be used to forecast possible coming heart problems [5], or to support a patient during CCR by offering guidance e.g. during an exercise. However, home CCR was not documented to be more cost effective than in-hospital CCR [6], but it would be beneficial for example when distances to clinics are long or patients have other difficulties to arrive to a hospital. Also adding more automation through technology to this process could increase cost efficiency.

Even though home telemonitoring seems to be a promising form of treating chronic diseases, more research is still needed especially regarding cost effectiveness, impact on the utilization of health services, and acceptance by health care providers [7]. We have addressed some of these issues in this paper.

As a part of the project, we interviewed different interest groups to evaluate a home CCR scenario [8, 10]. We also tested technical approaches with two different ECG monitors which had properties expected to be representative for ECG monitors available for use in home cardiac rehabilitation in the near future. We identified important technical issues that emerged from those interviews and depending on different scenario parts; we selected different signal processing methods to be evaluated. These alternative scenarios were divided into methods for off-line, real time, or local-real time analysis [9].

In this paper we present the results of the interview-based scenario evaluation mainly concentrating on technical issues. Additionally, we present the results from different signal processing methods which could be integrated in home cardiac monitoring, concentrating on central tasks, such as rejection of artifacts and quantization of ECG features.

II. METHODS

A. Scenario evaluation using interviews

Scenario evaluation consisted of two phases. In the first phase, an extensive heart patient scenario including technologies such as ambulance ECG, home monitoring and support group was created and evaluated by interviewing health care professionals and decision makers [8]. In this paper the results from the first phase are emphasized. In the second phase, focus group interviews were used to evaluate six shorter scenarios with different types of technologies to support independent living. Also the cardiac patient scenario was included, now focusing on home monitoring. Focus groups consisted of young adults, seniors and health care professionals. The heart patient scenario was rated average among the six [10].

B. Home ECG recordings

We used two different ECG recorders to simulate future wearable/portable home ECG monitor. The first device was developed at Tampere University of Technology (TUT) containing 2-channel ECG (sample frequency 200Hz, 8 bit resolution) and 2-channel accelerometers (sampled frequency 28.57 Hz, 8 bit resolution). Operating time was 24 hours and it had a Bluetooth data transfer possibility [11]. The second ECG monitor was Alive Heart Monitor (Alive Technologies, Queensland, Australia) with 1-channel ECG (sampling frequency 300 Hz, 8 bit resolution) and 3-channel accelerometer (sampling frequency 75Hz, 8 bit resolution).

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In analysis we used data collected during daily activities. 6 recordings were collected with the first device containing data over 8 hours and 40 minutes, and 3 recordings over 15 hours 30 minutes with the second ECG monitor.

C. *Signal processing methods for recorded ECG*

We made a state of art literature review (for example [12,13,14] were used) and based on that we selected possible methods to be tested in 1) artifact rejection, 2) heart rate calculation (detection of R –peaks), and 3) detection of other ECG parameter (such as T – and P-wave), being in practice the most relevant tasks for ECG interpretation. Central to the choice and evaluation of methods was implementability in simple (home) recording set-up.

In the artifact rejection task (1) we tested usefulness of Independent Component Analysis (ICA) [12] and Adaptive Filters [13]. Theoretical background of ICA can be found in [12]. The underlying principle is to separate from N signals, that contain a mix of different source contributions, into N signals of independent components, ideally separating (ECG) signal and noise into different components. In this case, the aim was to separate a clean ECG component signal from 4 recorded channels. For ICA analysis, FastICA software (Matlab implementation) provided by Helsinki University of Technology was used. The second method applied for the first task was linear adaptive filters using the least-mean squares (LMS) algorithm. These are a well-known and simple to implement concepts to decrease noise in non-stationary signals. The most popular form of an adaptive filter is the application of noise cancelling with reference input. The first idea was to use one of the accelerometer signals as a reference channel, using the notion that much of the noise in the ECG is caused by movements, which are strongly represented in the accelerometer signal. An alternative approach was to clean up one ECG channel by using the second ECG channel as a reference input.

In the second task (2) we compared different R-peak detection algorithms mainly to find the most reliable one and how do simple methods (less calculation) perform against more complex methods. We selected a) an open source algorithm based on the Pan and Tompkins QRS detection algorithm [14], b) an in-house developed R-peak detection algorithm with filtering of the R-peak intervals, c) algorithm developed in-house at TUT to detect R –peaks [11], d) simple curve-length based algorithm capable to fast processing [15], and e) R -peak interval recorder from Suunto Oy (Helsinki, Finland) as implemented in T6 heart rate meter. We have presented numerically the comparison from data recorded over 60 minutes during daily activity (45 minutes brisk walking, 15 minutes reading newspaper and putting shoes on), which we verified manually and used this as reference detections of R-peaks.

The third task (3) was to analyze capabilities of off-line processing software for ECG in these types of recordings. We selected to use an open source software package (PUWAVE) capable of detecting P, QRS and T waves from multilead ECG [14]. However, we used it to process only single-lead ECG.

III. Results

A. *Interviews*

In the interviews, the following observations were made regarding the technology described in the scenarios (letters help to associate between results of the interviews and signal processing in the discussion).

New technical solutions

a) could make it easier for the patient to make lifestyle changes which is often needed as a part of a treatment
b) could enable an earlier release from hospital to home
c) solutions have to be more cost effective compared to old processes in order to introduce them to public health-care (now already the lack of resources was mentioned as one of the biggest problem)
d) can be used to improve current diagnose making
e) should not consume more time in the care chain
f) requires to include education for the users when taking into use
g) can improve security of misuses (like e-recipe)
h) should be designed considering that one-fits-all idea does not work well in health-care
i) can not replace human contact totally
j) Used trend in health care is to outsource simple diagnostics which sometimes utilize technology (such as sleep apnea diagnosis and Holter monitoring)

Other issues:

k) In the public health care sector, decision-makers have strong authority, but information link to workers may be missing, and new practices penetrate to sector even though they might not be wanted.
l) Decision-makers have to consider also ethical aspects together with cost-efficiency.
m) Interviewees emphasized patient’s own responsibility in treatment (also responsibility of using new tools).
n) Where does the responsibility of the public health care end in the care chain? Should it pay for personal technology?
o) Organizations have already strong position to deliver for example rehabilitation and support group services, and they might be one sector to support with technology. (for example Finnish Heart Association)
p) Any negative experiences should be avoided with new technology (start with the most willing persons when piloting).

B. *Signal processing experiences*

When processing the ECG signal with ICA we noticed following difficulties which were partly known already: 1) one has to associate the ICA channels with their possible meaning by visually looking at the data, this is a problem in a real-time processing situation (in [12] this is done by using thresholds, based on the statistics of typical artifacts, but this is not feasible in this environment where a wide range of different types of

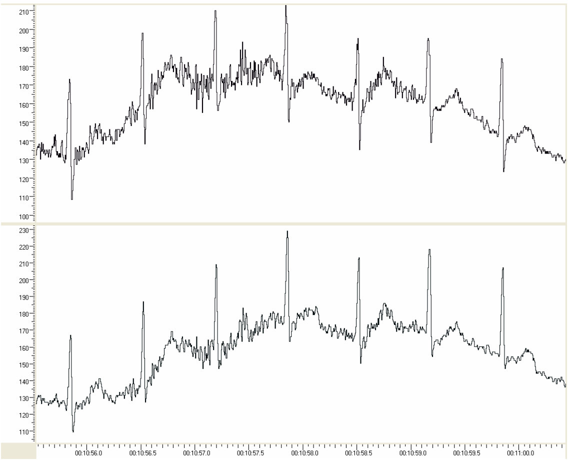

Figure 1: example from effect of adaptive filtering during an artifact, upper signal is original signal, and lower is after filtering (y-axis scale: 10mV, gain used in the recorder)

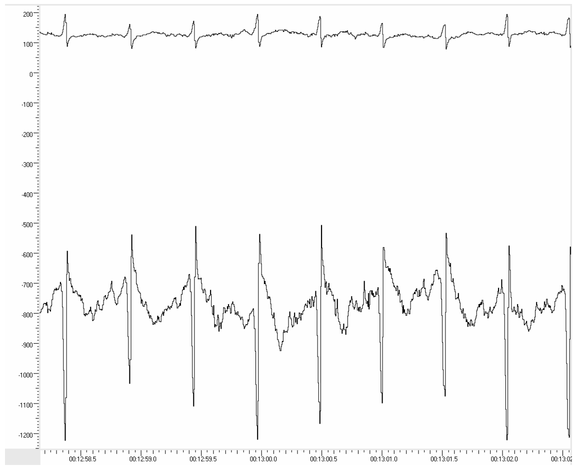

Figure 2: amplitude and sign changed in output of ICA, upper signal is original ECG waveform and lower signal is output of ICA (y-axis scale: 10mV, gain used in the recorder)

artifacts occurs) 2) absolute amplitude information (including +/- sign) is lost in the ICA signals (as seen in Fig. 2), which may be a problem for analysis. Moreover, 3) every time the ICA is run the results (order of the output signals) may be different, which is also problematic, since in a real-time application the signal will be analyzed in segments leading to repeated use of ICA.

With adaptive filters the first idea was to use the acceleration signal as a reference. This worked in the sense that it removed the very low frequency baseline fluctuations from the ECG effectively, but did not really improve the shape of the ECG complexes themselves.

The second alternative was to use both ECG channels. This gives better estimations in several cases. From the examples (Fig. 1) can be seen that for some periods this helps to restore the QRS complex. Baseline wandering is not removed in this set-up (because the baseline shift is typically present in both ECG channels at the same time).

A comparison of R -peaks detected by different algorithms are presented in Table 1. The data are not very difficult (60 minutes of normal daily routines such as sitting and walking) in this case but gives indication that also the simplest method (curve-length based) does provide reasonable results at a very low computational cost. True positive detections are ranging between 98.2% and 99.9%.

In the third processing task we made visual analyses how well the PUWAVE algorithm performs the detection of wave forms other than the QRS-complex. Fig. 3 shows representative example of the algorithm's capability to detect T and P wave. For a artefact-free signal the detection is reasonable accurate from single lead ECG (e.g. for interval calculation), but when the data quality decreases the number of wrong or missed detections is rapidly increasing.

IV. DISCUSSION

Interviewees emphasized the importance of finding out the true needs in health care for using the new technology. They also stated that lifestyle changes related problems are important in rehabilitation together with the fact that patients should take more responsibility of their own treatment. Based on this we suggest that simple ECG based monitoring device could help to give information and guidance to a patient during his/her rehabilitation. However, currently there is no widely accepted concept that uses this kind of an approach, except some data recording systems for diagnostics, e.g. detection of arrhythmias based on short use and off-line analysis such as Holter monitoring. Commercially available heart rate meters form a potential means to monitor a patient's heart (a, h, m; see section IIIA), but they are not currently directed to rehabilitation, although Suunto's T6 performed well in R -peak detection among the ECG based algorithms. Design of new technical solutions for rehabilitation could be adopted from heart rate monitor concept thanks to their high acceptance factor and reasonable price (b).

Cost efficiency and effects on work time were mentioned as important issues when designing new solutions to the field of healthcare (as in [7] also). There have been already some

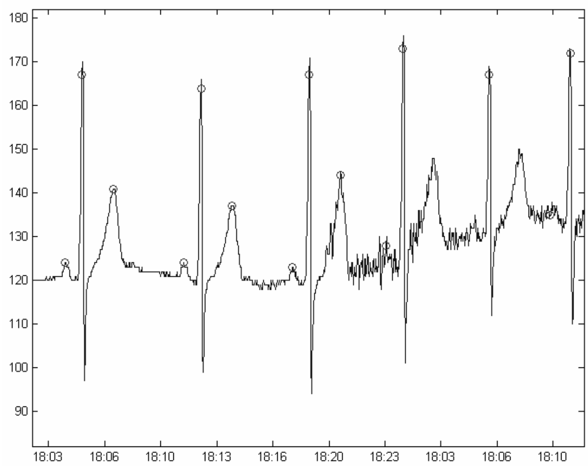

Figure 3: Example of PUWAVE output for good and bad quality ECG; output (circles indicating) of detected P, R, and T peaks. (gain used in the recorder)

TABLE I. ACCURACE OF R-PEAK DETECTION OF DIFFERENT ALGORITHMS : A (OPEN SOURCE), B (INHOUSE), C(TUT INHOUSE), D(SIMPLE), E(SUUNTO T6)

Algorithm	*A*	*B*	*C*	*D*	*E*
true positive %	99.77	99.85	99.21	98.19	99.77
false positive %	0.35	0.17	0.55	1.98	0.20

indications of telemonitoring being more cost efficient than usual care [16]. However, this has to be demonstrated more thoroughly before the public sector is willing to take these technologies into use. Automation of processes through technology as much it is realistic together with technology being easy to use and robust could decrease the work load of the health care personnel (d, e). This still needs lot of evidence for decision makers and actual need from the users.

We tested different methods to process data collected with cheap ECG home monitors. The tasks were artifact rejection, R-peaks detection and extraction of other waveform components of ECG. (b, c, m)

ICA is in principle a powerful method for analysing signals in general, but it may not be the most suitable in this artefact rejection task (hard to automate (e)).

In the case of adaptive filtering, when the acceleration signal was used as a reference we noticed that the acceleration curve doesn't seem to be represented very much in the noisy ECG other than for very low frequencies (basically tells is person active). To remove very slow components other, more simple methods are available. When another ECG channel was used as a reference, results showed that this could facilitate (automatic) recognition of the R-peak , but it should be kept in mind that this shape-changed signal should not be used for visual inspection by a cardiologist. For the adaptive filter implementation, in this case a Matlab version was used, but the algorithm is very simple and fast and can be implemented without much trouble on any platform (mobile or PC). (a, b, h)

In the R-peak detection task, more than 98% accuracy was achieved with all algorithms. Detection is difficult in case when there are large artefacts in the data – in those segments almost all the methods seem to make some mistakes, with the simplest algorithm making the most mistakes. However we did not implement the rules which analyze and possibly correct detections based on intervals between detected R-peaks in the simple algorithm. By adding this one could improve performance at the cost of extra computation. (e, p)

Some errors in detection of other ECG parameters imply that there should be some indication when the data quality is appropriate for reliable detection. It depends on the application how reliable the detection has to be, but for this specific application the method worked satisfactory. (d, j)

V. CONCLUSION

We noticed that health care concepts involving technology initiated a lot of discussion among health care professionals and decision makers, mostly regarding cost efficiency and improved care processes rather than technology. However, attitudes towards technology were generally positive when preceding conditions are fulfilled. Therefore, technology development will benefit from cooperating with health care professionals and users.

Quality of data, promising signal processing results, and affordable price were also encouraging information when we tested different ECG signal processing paradigms with simple, portable recorders. Smart combination of already developed technical methods, and good service concepts could have potential use in the cardiac rehabilitation.

REFERENCES

[1] www.who.int/en (accessed 27.11.2007)

[2] R. Taylor et al, "Exercise-Based Rehabilitation for Patients with Coronary Heart Disease: Systematic Review and Meta-analysis of Randomized Controlled Trials",The American Journal of Medicine, vol. 116, pp.682-692. May 2004

[3] M. Williams et al, "Clinical evidence for a health benefit from cardiac rehabilitation: An update.", American Heart Journal, vol. 152, pp. 835-841, Nov 2006

[4] K. Kotseva, D.A. Wood, D. De Bacquer, J. Heidrich, G. De Backer,"Cardiac rehabilitation for coronary patients: lifestyle, risk factor and therapeutic management.Results from the EUROASPIRE II survey", European Heart Journal Supplements, vol. 6, pp. J17–J26, 2004

[5] G. Lanza, "The Electrocardiogram as a Prognostic Tool for Predicting Major Cardiac Events", Prog Cardiovasc Dis. vol. 50, pp.87-111, Sep-Oct 2007

[6] R. Taylor et al, "Home-based cardiac rehabilitation versus hospital-based rehabilitation: A cost effectiveness analysis?.", International Journal of Cardiology, vol. 119, Issue 2, pp. 196-201

[7] G. Paré, M. Jaana, C. Sicotte, "Systematic Review of Home Telemonitoring for Chronic Diseases: The Evidence Base "J Am Med Inform Assoc, vol. 14 , pp. 269-277, Jun 2007

[8] T. Petäkoski-Hult et al, "Technical solutions supporting the rehabilitation activities at home", 9th Congress of EFRR (European Federation for Research in Rehabilitation), Aug 2007

[9] J. Rodriguez, A. Goni, A. Illarramendi, "Real-Time Classification of ECGs on a PDA", IEEE Transactions on Information Technology in Biomedicine, vol. 9, pp. 23- 34, Mar 2005

[10] O. Kenttä, J. Merilahti, T Petäkoski-Hult, V. Ikonen,I. Korhonen, "Evaluation of Technology-Based Service Scenarios for Supporting Independent Living", Proceedings of the 29th Annual International Conference of the IEEE-EMBS 2007, pp. 4041-4044

[11] E. Hyvärinen, I. Ruuskanen I, J. Hyttinen, J. Kaihilahti, O. Vainio, "Mental stress analysis instrumentation and tools based on heart rate variability." Analysis of biomedical signals and images 18th international EURASIP conference Biosignal 2006 :proceeding. pp. 196-198.

[12] T He, G Clifford, L Tarassenko, "Application of independent component analysis in removing artefacts from the electrocardiogram" Neural Computing & Applications, vol. 15, Apr 2006

[13] N. Thakor, Y Zhu, "Applications of Adaptive Filtering to ECG analysis: Noise Cancellation and Arrhythmia Detection." IEEE TBME, vol. 38, pp. 785-794, 1991

[14] P. Laguna, R. Jané, P. Caminal, "Automatic detection of wave boundaries in multilead ECG signals: Validation with the CSE database", Computers and Biomedical Research, vol. 27, pp. 45-60, 1994.

[15] C. Marchesi, M. Paoletti, "ECG Processing Algorithms for Portable Monitoring Units". The Internet Journal of Medical Technology, vol. 1, 2004

[16] J. Cleland, A. Louis, A Rigby, U. Janssens, A. Balk, "Noninvasive home telemonitoring for patients with heart failure at high risk of recurrent admission and death: The Trans-European Network-Home-Care Management System (TEN-HMS) study." J Am Coll Cardiol. vol. 45, pp.1654–64, May 2005