Detecting Patient's Emergency - a Minimum-Computation Procedure for Pervasive Cardiac Monitoring

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***Abstract*—Searching for the economy and opportunities for applications of human experience yielded a development of a request-driven ECG interpretation method. It assumed the processing of the acquired ECG is triggered by the data validity period expiry or by the emergency detector continuously supervising basic parameters of the signal. This paper focus on the correct choice of the emergency detector procedure covering a wide range of diseases but not requiring much computational power in the patient-side wearable system. After the investigation of numerical complexity of the initial stages of ECG processing and representation of most common diseases in basic cardiac parameters, we propose a short-term rhythm index as an emergency indicator. The computation is simple enough to be performed in a limited-resources environment (e.g. cell phone) without considerably influencing its autonomy time.**

I. Introduction

THE formulation and implementation of the individual data variability periods for principal cardiac parameters led to prototyping of request-driven ECG interpretation scheme. This modality is particularly interesting for networks of pervasive cardiac monitoring, since avoiding the unnecessary signal processing significantly extends the autonomy time of the patient-side wearable recorder. An additional advantage was the cost-effective management of data transmitted via digital wireless channel to the surveillance center [1].

The adaptive processing of the ECG signal in a remote recorder was triggered by the expiry of validity time of previously calculated parameters and by the emergency detector. This idea mimics a typical patient-doctor relationship. It assumes irregular medically-justified examinations initiated on a background of patient status as described by the medical parameters or as subjectively perceived by the patient as the lack of wellness (e.g. pain). The validity time as a principal interpretation trigger includes the past description of patient status. Depending on the patient status, the system dynamically builds a hierarchical list of the diagnostic parameters demanded in next future including the medical relevance and data validity period attributes.

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The adaptivity of the irregular ECG processing needs the secondary trigger in case of emergency. From the system's point of view, the patient is well and the data validity periods are set relatively long, thus interpretations are rare. Unfortunately, in cardiology sudden occurrences of disease symptoms are common and for the patient safety it is worth an effort to capture these events. The simplest option present since decades in every Holter recorder is a "patient button", in newer loop-recorders triggering the recording and interpretation of a signal strip [2]. Although the presence of a button is required by international standards [3] and we had to maintain its functionality, in our opinion the system performance should not rely on subjective perception of pain or "something uncommon". This raises the necessity of a continuously running limited-scale ECG interpretation procedure calculating a meta-parameter used as a secondary trigger of ECG processing in case of emergency. The role of this procedure is analogical to perception of the pain, it simply detects abnormalities in the signal. Unlike the pain, however, the automatic trigger is reliable, objective and doesn't require human interaction.

Even if data validity periods are estimated as relatively long, the system has to support sudden changes in patient's conditions (fig.1). The emergency detector consists of significantly limited set of interpretation procedures and meets two contradictory criteria:

- issues a meta-parameter shortening the validity period of any diagnostic parameter,
- in computational aspect is as simple as possible and preferentially uses only initial stage subroutines of the interpretation chain in order to maximize the reliability.

Having medical standards, examples of open-source software and few cardiology experts opinions as a background we initially proposed the heart rate variation as a parameter most suitable for emergency detection [4]. In course of further research we had to return to this point in order to optimize the ratio of detector efficiency to the computational complexity. This issue is presented in details throughout this paper.

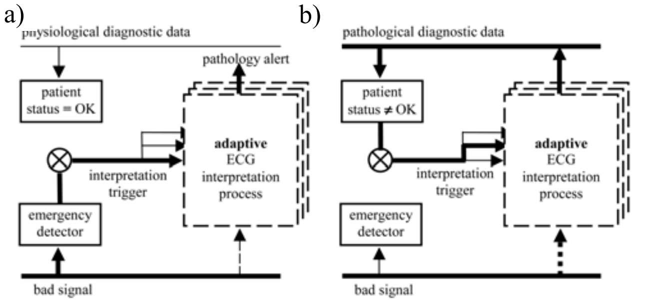

Fig.1 The detection of sudden abnormality occurrence; (a) data validity periods are long corresponding to physiological data, emergency detector triggers the interpretation which issues pathology alert; (b) pathological diagnostic data shortens data validity periods and triggers the interpretation more frequently.

II. Materials and Methods

A. Estimating the procedure complexity

Standard estimates can be used for assessment of the computational complexity of the ECG interpretation procedures [5]. In fact there is no unique approach to the algorithm and implementation of subsequent analysis steps and often the steps are not precisely separable. The research was also complicated by various manufacturers' policies concerning the software: some procedures are available as source files (usually C++), some as compiled libraries designed for a specific CPU family and several companies did not even respond to our scientific survey. Nevertheless our research is intended to future software developers and the generality of our findings is not affected by not including all software currently available on the market.

The effectiveness of the procedure is also influenced by the usage of platform-specific resources (commands, registers), which is much less unified in mobile computing devices than in desktop computers. Therefore we can't rely on the theoretical assessment of the computational complexity without verifying the calculations in laboratory. Certainly we had to limit the range of mobile platforms tested and our final choice was the development kit of the PXA-270 CPU [6] (fig. 2.). The PXA27x microprocessor family with a widely updated XScale core, is Marvell's implementation of the fifth generation of the ARM architecture, (code-named Bulverde). The PXA270 is clocked in four different speeds: 312 MHz, 416 MHz, 520 MHz and 624 MHz and is a stand-alone processor with no packaged memory. It is an integrated system-on-a-chip microprocessor for high performance, dynamic, low-power portable handheld and hand-set devices. It provides excellent MIPs/mW ratio of 4.625 at 150 MHz falling to 1.6 at 600 MHz. Currently it is used in a series of handheld computers (e.g. the Asus P-565, the Sharp Zaurus, the Motorola A780, the Acer n50, the Compaq iPaq 3900).

Fig. 2 The overview of PXA-270 XScale processor board (actual size: 67.6 x 36.7 x 5.2 mm).

B. Correlation of disease and parameter variability

Studying the ECG interpretation guidelines issued by several professional associations of cardiologist (e.g. AHA [7]) one can establish the relationship between the heart diseases and the variability of diagnostic parameters. Because various standards are in use, we found reasonable inspecting the archive records in order to estimate how far were the values of particular diagnostic parameters from their normal values for several most frequent diseases. Taking into account the probability of particular disease in the population we could estimate the reliability of the emergency detector based on selected diagnostic parameter. As the total of N archive records represent the diseases in live-acquired proportion, the average standard deviation of the parameter between the "normal" e^n and "abnormal" e^a part of the record or two different records of the same patient was taken as first estimate of variability index VI^e

$$VI^e = \frac{1}{N}\sum_{i=1}^{N}\left|e_i^n - e_i^a\right| \tag{1}$$

The research was aimed at finding a parameter e_1 with maximum VI index and other parameters e_n representative for diseases, but independent on the previously selected. In this research the variability index was weighted by the inverse of absolute correlation values making preference for uncorrelated parameters:

$$\begin{gathered} e_1 = \max_e (VI^e) \\ \forall n : e_n \notin \{e_1, e_{n-1}\}\ e_n = \max_{e_k : k \notin \{e_1, e_{n-1}\}} (VI^e) \cdot \\ \cdot (1 - |c_{n,n-1}|) \cdot (1 - |c_{n,n-2}|) \cdot \dots \cdot (1 - |c_{n,1}|) \end{gathered} \tag{2}$$

C. Compound emergency indicator

The approach presented as far was simplified by assuming the independence of diagnostic parameters in use. In fact all diagnostic parameters are derived from the signal and procedures at the front of processing has impact on the series of different parameters. On the other hand it would be naïve to expect that one diagnostic parameter was an emergency indicator sensitive enough in wide range of diseases. Therefore we assume that the emergency indicator EI would be a compound parameter calculated from several meta-data $e_1...e_n$ available in course of the ECG interpretation process.

$$EI = \sqrt{e_1^2 + e_2^2 + \ldots + e_n^2} \quad (3)$$

It should meet the following criteria:

- Representation of wide spectrum of most frequent heart diseases with consideration of the acuteness,
- Minimum calculation costs

First requisite assumes the research of disease-dependent ECG parameters variability in context of disease implications and occurrence probability. To cover wide range of diseases of various origins, the compound indicator includes several meta-parameters selected by their minimum correlation.

The calculation costs are usually expressed in instructions or in time units, however for wearable systems supporting the active power management it would be practical to express the calculation costs directly in power units (micro Watts). Such estimate is helpful to assess the impact of calculations made by the emergency detector procedure on the shortening of the wearable recorder autonomy time.

III. Results

A. Estimating the procedure complexity

Where source code was available, the complexity for each of selected ECG interpretation procedure was estimated in theoretical way as most probable count of machine cycles This value multiplied by power requirement per machine cycle given in a data scheet yields the estimate of power required for each specific procedure. For several procedures we had multiple algorithms available and in such cases the average value is presented in table 1.

Tab.1 Results of the investigation of procedure complexity (10s of ECG signal sampled at 500Hz, avg. HR=78 bpm)

procedure purpose (in ascending order)	implementation variants	theoretical complexity	required power [μW]
heartbeat detection	4	785000	169.7297
baseline estimation	2	115000	24.86486
heart rate estimation	2	700	0.151351
heartbeat classification	3	38760	8.380541
waves measurement	2	1320000	285.4054
axis determination	1	168000	36.32432
dominant rhythm detection	2	208800	45.14595
arrhythmia detection	1	14760	3.191351
SUM		**2651020**	**573.1935**

B. Representation of diseases in parameters variability

This point of research aims at finding the diagnostic ECG parameters that varies with a wide range of diseases. As a result of our previous study [8], we indicated twelve cardiac diseases as most common in the population tested. The archive records were scanned for the most "universal" diagnostic parameter changing its value in correlation $e_1...e_n$ with the pathology for possible wide range of abnormalities. The research results are displayed in table 2.

Tab.2 Results of the research of correlation of ECG parameters with most common heart diseases

disease	e_1 - heart rate variations	e_2 - contour variations	e_3 - wavelength variations
normal sinus rhythm	0.05	0.11	0.07
sinus tachycardia	0.67	0.12	0.22
sinus bradycardia	0.71	0.14	0.28
probable AV block	0.31	0.41	0.27
ventricular escape beats	0.44	0.81	0.31
atrial fibrillation	0.33	0.08	0.12
AV conduction defect	0.27	0.25	0.20
myocardial infarction	0.20	0.37	0.37
atrial enlargements	0.12	0.27	0.28
ventricular hypertrophies	0.08	0.42	0.35
left bundle branch block	0.11	0.27	0.21
right bundle branch block	0.14	0.31	0.33

C. Research for best representation of emergency

The results summarized in table 2 were used to estimate the coverage of various cardiac defects by the unambiguous response of the emergency detector. For the purpose of research, we expected the EI^e to be equal or greater EI^n+**std**(EI^n), where EI^e is the value of emergency indicator (see 3) for the diseases, EI^n is the value of emergency indicator for the normal signal and **std** is the standard deviation. The probability of missing an emergency event using simple and compound emergency indicator is presented in table 3.

Tab.3 Results of the research of optimal compound emergency indicator (10 s @ 500Hz, avg. HR=78 bpm)

disease	e_1	e_1 & e_2	e_1 & e_2 & e_3
true positive	17412	17550	17612
true negative	89076	89140	89204
false positive	1220	1098	989
false negative	890	810	793
sensitivity	0.951371	0.955882	0.956914
specificity	0.986489	0.987832	0.989035
positive predict. value	0.934521	0.94112	0.946831
theoretical complexity	900700	1107460	2427460
required power [μW]	194.7459	239.4508	524.8562

D. Convergence tests of fixed and adaptive interpretation results

The adaptive interpretation is expected to issue diagnostic results which quality is corresponding to the results of fixed methods. As a general estimate of convergence quality, we propose the value Q being a weighted sum of relative error of 12 most frequently used diagnostic parameters (HR, rhythm estimate, wave lengths and axes etc.). Weighting coefficients are calculated on a background of the use statistics and their sum is normalized to 1.

$$Q = \sum_{i=1}^{12} \Delta p_i \cdot w_i \text{ , where } \sum_{i=1}^{12} w_i = 1 \qquad (4)$$

Results for the general quality of diagnostic data issued by the request-driven ECG interpretation for sample sudden cardiac events simulated in test signal are summarized in table 4.

TAB.4 RESULTS FOR THE GENERAL QUALITY OF DIAGNOSTIC DATA ISSUED BY A REQUEST-DRIVEN ECG INTERPRETATION

transient simulated in the ECG signal	Q initial value [%]	Q final value [%]	delay to 120% of final Q value [s]
normal → atrial fibrillation	19.1	2.4	6.7
normal → ventricular tachycardia	56.3	4.7	3.5
normal → ST-depression (150μV)	14.7	1.1	12.2 *)
normal → bigeminy	27.4	0.7	3.8
normal → persistent supra ventricular tachycardia	22.1	1.3	5.8
normal → acute myocardial infarction	12.8	2.2	5.5

*) not detected as emergency

IV. DISCUSSION

The request-driven ECG interpretation concept based on individual data validity periods was prototyped and partially tested with use of standard database-originated signals representing various medical contents and events.

As a final conclusion we opt for the use of composed emergency indicator using heart rate variations (e_1) and contour variations (e_2). The additional use of wavelength variations (e_3) is not recommended, as it doesn't significantly improve the detector reliability, but increases the power requirements up to 524μW, which is a value not far from the power consumption of the complete basic ECG interpretation process. The use of heart rate and contour variations is very effective because their low correlation and thus high mutual independence. It is clearly visible in table 2 that diseases highly correlating with rhythm variations are not overlapping with those correlating with contour variations. From the same table the poor efficiency of wavelength variations can be explained. This parameter, although computationally expensive, doesn't correlate well with any of twelve most common heart failures (maximum correlation of 0.37 with myocardial infarction).

Our research proved how little power is required for the analysis of 10s strip of single channel ECG. The best case power consumption is estimated as little as 0.5 mW. This was achieved thanks to the use of a powerful microprocessor at a low clocking rate. Unfortunately, in a real wearable interpreting system, the maintenance of operating system, the memory power supply, the telecommunication module and the analog electronics will multiply the power requirements.

In author's opinion, adaptive systems using request-driven interpretation, except for technical advantages are closer to the human reasoning. They provide prioritized and accurate patient report at the moment it is expected.

REFERENCES

[1] P. Augustyniak "The Use of Selected Diagnostic Parameters as a Feedback Modifying the ECG Interpretation" Proc. Computers in Cardiology (IEEE-EMB), Vol 33, 2006, pp. 825-828

[2] W. Zareba, P. Maison-Blanche, E.H. Locati "Noninvasive Electrocardiology in Clinical Practice" Futura Publishing Co. New York, 2001.

[3] IEC 60601-2-51. "Medical electrical equipment: Particular requirements for the safety, including essential performance, of ambulatory electrocardiographic systems." 2001

[4] P. Augustyniak "Request-Driven ECG Interpretation Based on Individual Data Validity Periods". Proceedings of the 28th IEEE EMBS Annual International Conference Lyon, France, 2007, pp. 3777-3780.

[5] C.H. Papadimitriou "Computational Complexity". Addison-Wesley, 1994.

[6] http://www.toradex.com/e/Factsheet_Colibri_Intel_Marvell_XScale_PXA_Computer_Modules.php (visited on March, 31, 2008)

[7] AHA ECG database. Available from Emergency Care Research Institute, 5200 Butler Pike, Plymouth Meeting, PA 19462.

[8] P. Augustyniak "Pursuit for the Knowledge of a Cardiology Expert – a Hidden Poll Methodology" submitted for IEEE-EMBS 2008 Conference.