Request-Driven ECG Interpretation Based on Individual Data Validity Periods

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Abstract—Traditional approach to the automated ECG analysis assumes the calculation is triggered for each data point acquired in a uniform time interval. This approach reveals the variability of selected diagnostic parameters differing by more than three orders. Distributed systems using global wireless digital communication may benefit from this difference using variable reporting interval or data-adaptive report content. More natural consequence is a request-driven interpretation described in this paper. Our approach assumes the processing of the acquired ECG is triggered by the data validity period expiry. Such solution significantly reduces unnecessary computation and is particularly interesting in aspect of wearable devices autonomy. Correct definition of data validity for each particular diagnostic parameter guarantees the completeness of the patient status and its convergence to the result of traditional approaches.

I. INTRODUCTION

IGITAL processing and automatic interpretation of vital signs are currently vital scientific interests, and are considered as emerging technologies for health monitoring and early detection of life-critical events. Early solutions of wearable cardiomonitors took the advantage of microelectronic technology, but functionally followed bedside interpretive electrocardiographs [1-6]. Similarly, surveillance networks were conceptually closer to a group of independent cardiologists than to a hierarchy established during the history of medicine [7]. Moreover, the traditional approach assumes the uniform time-interval signal acquisition and unconditional processing including all available stages. In majority the processing branches end up with a conclusion of no relevant changes since precedent diagnostic report, because the variability of diagnostic parameters is much lower than the variability of the signal itself.

Our investigation on non-uniform signal representation [8] and irregular reporting in the wireless cardiac monitoring network [9-10] concluded with the estimation of specific band limit value for each basic diagnostic parameter. The bandwidth itself is also variable and depending on the patient status. Generally writing, the worse patient status implies more frequent reporting necessity.

The concept of adaptive ECG interpretation and reporting is based on prioritized irregularly timed request for diagnostic parameters. That concept was consequently developed to a request-driven ECG interpretation method presented in this paper. It considers two issues crucial for wearable devices with a wireless connection: maximized autonomy and minimized transmission channel costs.

Main novelty of our method consists in irregular ECG processing triggered and defined by two sources:

- patient status,
- emergency detector.

These sources launch in the remote recorder a subset of interpretation subroutines necessary to provide the request for diagnostic parameters (fig. 1). The unnecessary processing is limited, thus the interpretation is relatively fast and the outcome contains highly relevant data transmitted in smart packets.

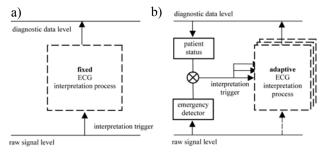


Fig. 1 Main principle of request-driven ECG interpretation (a) traditional interpretation scheme (b) request-driven interpretation scheme

Besides the economical aspect, additional advantage of this approach is a closer simulation of a human expert behavior.

II. MATERIALS AND METHODS

A. Estimating and using data validity periods

Human experts usually perform hypothesis-driven interpretation tasks sequence and limit the diagnostic set to the most relevant results. The introduction of data priority attribute adapted to diagnostic goals has significant impact on automatic interpretation process, in aspect of economy and similarity to the human reasoning.

The appropriate selection of the update interval or data validity period is an extension of the data priority concept. Depending on the data variability and current patient status,

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each component of the diagnostic result has to be calculated and transmitted not earlier than its validity period expires. In cardiology, an example of high frequency parameter is the heart rate (HR), while an example of low frequency parameter is the ST-segment depression.

Data validity periods are estimated by a supplementary cross-reference procedure and included in the diagnostic parameter set. Unfortunately, no currently available medical information storage and interchange standard provides data fields of such type.

B. Patient status as interpretation trigger

The datatype-specific validity periods depend on the patient status represented in the parameter under consideration and other parameters as well (fig. 2). Detailed investigation of correlations between diagnostic parameters and multidimensional nonlinear regression describing their contribution to the data validity period exceeds the framework of presented research. For example, the QT dispersion has to be reported once per 5 minutes while it values fall in the physiological norm, otherwise the reporting frequency should be increased up to the beat-to-beat rate.

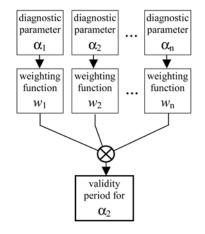


Fig. 2 Cross-dependence scheme of validity period for diagnostic parameter α_2 and current values of diagnostic parameters

Since the patient status-dependent datatype-specific validity periods are main source of interpretation trigger, all relevant parameters should be calculated in real time upon the availability of diagnostic parameters and send back to the processing chain.

C. Emergency detector as interpretation trigger

Even if data validity periods are estimated as relatively long, the system has to support sudden changes in patient's conditions. 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 finally selected the heart rate variation as a parameter most suitable for emergency detection. Figure 3 demonstrates two stages of emergency detection.

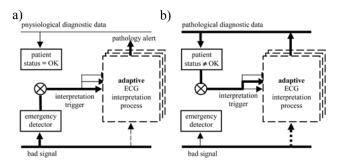


Fig.3 The detection of sudden abnormality occurrence; (a) data validity periods are long corresponding to physiological data, emergency detector triggers the interpretation which issues pathology alert; (b) pathological diagnostic data shortens data validity periods and triggers the interpretation more frequently.

D. Propagation of interpretation request

In a prevalence of regular systems, the acquisition of data point occurs in regular time interval and triggers computation of all parameters. In a system with variable data validity intervals the triggering procedure works individually for each diagnostic procedure and is located at the end of the corresponding processing path. Since the path usually contains multiple procedures in chain, each data request implies the use of existing metadata as long as within their validity period, or otherwise is transmitted to the previous procedure (fig. 4). For some metadata the validity period is longer than for the final data, thus only a fraction of the triggers achieves the beginning of the processing chain avoiding the unnecessary processing of huge amount of raw data.

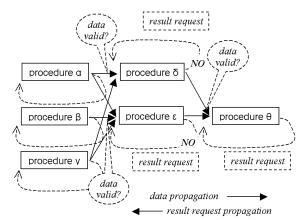


Fig. 4 Scheme of the asynchronous computing

III. TESTS OF THE METHOD AND SIMULATION RESULTS

A. Defining the software behavior

Testing the prototype of request-driven ECG interpretation required limiting the diagnostic parameters set and the patient's status set. Since the investigation of proper reporting contents and frequency as dependent on patient condition is still not concluded, we had to make assumptions on required reporting frequency for each parameter separately (tab. 1).

TAB.1 EXCERPT OF THE CROSS-REFERENCE TABLE DESCRIBING THE DATA VALIDITY PERIOD AS A FUNCTION OF PATIENT CONDITION

parameter validity period	patient status estimate				
rt [s]	heart rate	rhythm type	extrasystoles	PQ-interval	
rhythm type	>110 bpm,	normal: rt = 60	absent: rt = 60	>180 ms	
	rt = 160-HR	atrial:	atrial:	rt = 240-PQ	
	<60 bpm,	junct.: rt = 10	junct.: rt = 5	< 60 ms	
	rt = 3*(HR-40)	ventric.: rt = 3	ventric.: rt = 2	rt = PQ	
heart rate	>100 bpm,	normal: rt = 30	absent: rt = 30		
	rt = 55-HR/4	atrial:	any: $rt = 1$		
	<60 bpm,	junct.: rt = 10		-	
	rf = HR-30	ventric.: rt = 3			
wave axis		normal: rt = 60	absent: rt = 60	$\Delta PQ > 40ms$	
		atrial:	any: rt = 1	rt = 1	
	-	junct.: rt = 5		$\Delta PQ > 15ms$	
		ventric.: rt = 1		rt = 15	

Although medically justified weighting functions (see fig. 2) may have to be corrected in the future, all technical aspect of request-driven interpretation algorithm, its correctness and feasibility are demonstrated here.

B. Test signals for validation of adaptive interpretation

Adaptive interpretation methods are recently introduced and were not considered by worldwide-recognized standard databases. These databases contain annotated examples of specific pathologies but transient or sudden events are rarely represented. Therefore, ECG test signals representing various pathologies were artificially combined from several strips of original MIT-BIH [11] database recordings.

C. Uniformization of the diagnostic outcome

For the lack of guidelines on testing the adaptive ECG interpretation software, we applied our custom test procedure taking the diagnostic outcome of fixed software as the reference. Direct comparison of values was not possible, because the diagnostic outcome of the adaptive system is non-uniform, i.e. each parameter is updated at different time point with the frequency varying in function of previous estimates of the patient status.

The diagnostic outcome of the adaptive interpretation being non-uniformly sampled time series $N_j(\{n, v(n)\})$ was first uniformized with use of the cubic spline interpolation [12] given by a continuous function:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3 \quad (1)$$

 $x \in [x_i, x_{i+1}], i \in \{0, 1, \dots, n-1\}$ best fitted to the time series N_j .

The interpolation yielded the uniform representation of

each parameter by sampling the $S_i(x)$ at the time points *m* corresponding to the results of the fixed software:

$$N'_{j}(m) = \sum_{m} S_{i}(x) \cdot \delta(x - mT)$$
⁽²⁾

These points in turn were compared to the reference.

D. Request-driven interpretation testing areas

The fixed interpretation software is usually tested for yielding the results within the tolerance margins specified on a physiological background. In adaptive software, more interesting is the dynamic aspect of adaptation and thus new parameters should be added to the global estimate of method performance:

- convergence delay and coherence of fixed and adaptive interpretation results,
- static divergence of uniformly reported fixed interpretation results and their sparsely reported counterparts from adaptive interpretation,
- disease-domain sensitivity of emergency detector,
- technical and economical advantages of requestdriven ECG interpretation,
- correctness of data validity periods estimation.

Since these areas and appropriate test methodology are rarely reported in the literature, we focus mainly on the delay and coherence test and technical advantages estimation in this paper. The others require additional research on medical background and are considered for future works.

E. 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. Comparing the diagnostic data quality is a complex issue, which needs consideration of:

- dependence of convergence delay and final coherence on the stimulus represented in the ECG signal alteration and on the precedent configuration of the interpretation process,
- different convergence properties for particular diagnostic parameters,
- different medical relevance of adaptation delay and final divergence between particular parameters and corresponding reference.

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.

$$Q = \sum_{i=1}^{12} \Delta p_i \cdot w_i$$
, where $\sum_{i=1}^{12} w_i = 1$ (3)

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 2.

TAB.2 RESULTS FOR THE GENERAL QUALITY OF DIAGNOSTIC DATA ISSUED BY A REQUEST-DRIVEN \mbox{ECG} interpretation

transient simulated in the ECG signal	Q initial value [%]	Q final value [%]	delay to 120% of final Q value [s]
normal \rightarrow atrial fibrillation	19,1	2,4	6,7
normal → ventricular tachycardia	56,3	4,7	3,5
normal \rightarrow ST-depression (150 μ V)	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 \rightarrow acute myocardial infarction	12,8	2,2	5,5

*) not detected as emergency

Other performed tests aimed at estimating technical and economical advantages of request-driven interpretation. We assumed that the adaptive interpretation and emergency detector are implemented in a wearable battery-operated device connected via digital wireless communication channel with the server collecting diagnostic results and issuing requests. The pursued advantages consisted in reduction of resources (i.e. processor time) and transmission channel use in comparison to the fixed interpretation method. The results highly depend on the signal contents, thus in table 3 they are summarized for sample test signals.

TAB.3 ESTIMATES OF TECHNICAL AND ECONOMICAL ADVANTAGES OF REQUEST-DRIVEN ECG INTERPRETATION

medical contents	processing	transmitted	processing
represented in the ECG	complexity	data volume	time
signal	[%]*)	[%]	[%]
normal	22	12	27
atrial fibrillation	25	25	37
ventricular tachycardia	33	17	40
ST-depression (150µV)	25	28	39
bigeminy	27	25	37
persistent supra ventricular tachycardia	37	33	42
acute myocardial infarction	57	40	85

*) including the emergency detector thread

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. In course of reported research we faced many challenges and unprecedented issues implied mainly by the adaptivity of the ECG interpretation process. Some of the questions were directed to the cardiologists and need intense research in the future, e.g. proper reporting contents and frequency as dependent on patient's condition. The lack of medical knowledge and detailed procedures that could be taken as reference, caused us to postpone tests and estimates of some important features available in the adaptive algorithm. In spite of some limitations, our research contribute to the very hot topic of automatic distributed vital signs-based surveillance with several interesting remarks:

- Demonstrates the feasibility of an adaptive interpretation system triggered by the data request based on variable validity period depending on data type and value.
- Considers the scenario of emergency and describes the system behavior necessary to a prompt support of life-critical events.
- Defines the area of testing the diagnostic parameters quality in case of adaptive systems.

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.

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