electrocardiogram interpretation,
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OPTIMIZING THE MACHINE DESCRIPTION OF ELECTROCARDIOGRAM

The electrocardiogram is a digital record of effective action potencials of heart muscle fibres, thus it contains an important information about the heart function. Unfortunately, the signal theory-based dscription of the ECG contents is not efficient in extracting these data, and the practical interpretation software is mostly based on heuristic statements. This conclusion was a motivation for our research on the expert-like machine reasoning based on ECG perception analysis, physiology-driven feature extraction and fuzzy logic. This paper highlights the aspect of optimal description of an electrocardiogram contents in a digital record.

1. INTRODUCTION

Intrinsic nature of the ECG and other biomedical signals includes high inter-personal variability of waveform combined with irregular medical importance of the record's sections. Usually, a very meaningful episode is not easy to distinguish among of hours of useless data. Heuristic algorithms designed for the bedside ECG recorders process usually short records and when adapted to long term (e.g. Holter) diagnostics lack of flexibility in extracting medical features of the signal. In such systems the automatic ECG interpretation needs the expert assistance for corrections of missed heartbeats, manual waves assignment or parameters adaptation, which is widely accepted for off-line processing.

Another challenge for machine-based ECG interpretation is the remote monitoring of life-critical parameters (Fig. 1), which is recently one of the most focused topic in the developed societies [4, 6]. In such applications, the expert which can not be present close to his patient should be provided with the most accurate data. Recently, the majority of remote monitoring systems assumes a direct transfer of acquired vital signs to the interpretation center. Leaving apart the cost of communication channel, the cardiologist is not supported in management of huge amount of data and in consequence more exposed to the risk of interpretation mistakes [3, 5].

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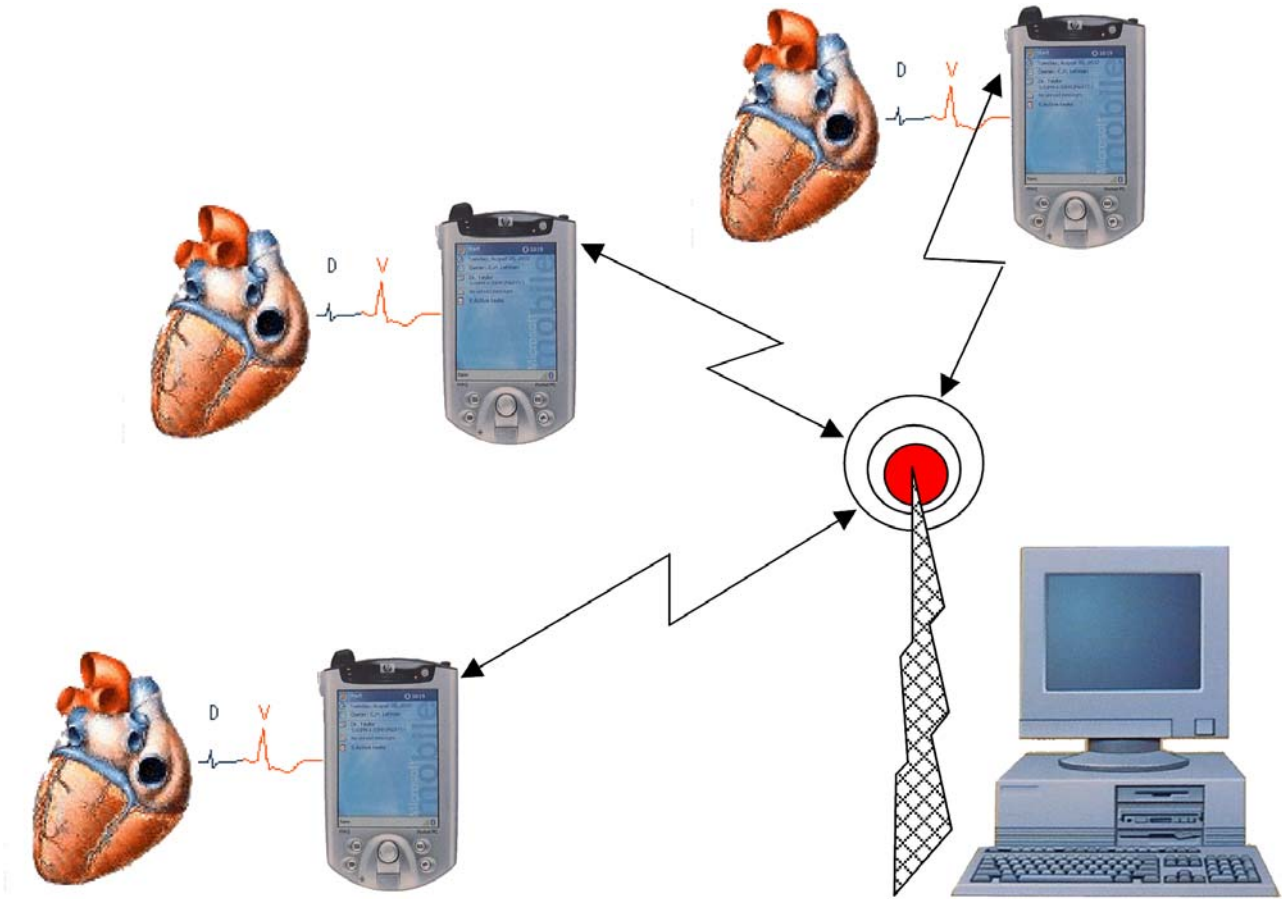

Fig. 1 Architecture of remote monitoring network for cardiology

These remarks justify the idea of spread ECG interpretation made by patient-side worn computer as the most appropriate approach. Additional feature is the opportunity to accustom the interpretation software as it best adapts to the signal variability from patient to patient. The spread interpretation, however, needs the description of communication standards between the centralized and remote intelligence. The essential part of these standards is an optimal machine description of electrocardiogram concerned in this paper. The optimization criteria include:

- maximum fidelity of medical contents
- limitation of data processing in a wearable computer
- minimum data stream

The machine description of electrocardiogram is automatically derived from the original signal [8] with a significant reduction of its size (Fig. 2). It does not contain the interpreted data, thus it is not limited by the processing software, however the processing takes into account all possible medical aspects of the raw signal rather than its technical features. The optimal description of the ECG contents is expected to be sufficient for calculations of diagnostic parameters identical to those obtained from the raw signal, although the reproduction of original ECG is not intended. Therefore, its quality shall be judged by distortions in the domain of diagnostic parameters instead of the domain of signal space.

The areas of application extend far beyond the remote monitoring. Making a diagnostically representative fingerprint of the ECG contents is expected to have an impact on the following aspects of health record management:

- database searching and comparing
- hardware and software adaptation to the patient's features and situations (e. g. sleeping, awaken)
- adaptation for the diagnostic goals variability

The last option opens an unexplored area in the domain of medical decision making and automated support, as the communication technology offers an opportunity for manual or automatic alteration of the remote monitor function while the monitoring is in progress.

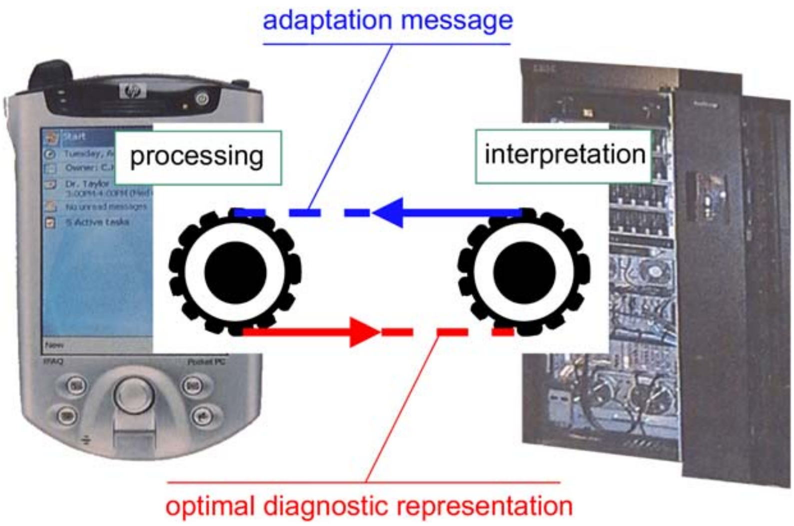

Fig 2. Scheme of information interchange between the server and remote monitors

2. MATERIALS AND METHODS

The machine description of electrocardiogram contains all meta-information interfacing the non-assisted signal interpretation routines and the manual or semi-automatic diagnostic decision making. Although the goal is reproducing the expert reasoning as far as possible in a computer algorithm, there are several approaches to establish the final data set included in the optimal ECG description.

2.1. EXPERT-MACHINE LEARNING

The computer algorithm calculates parameters d being a quantitative description of the waveform in the n-dimensional diagnostic domain $\boldsymbol{D}^n$. The parameters are well defined on physiological background, but not easy to derive properly from the unknown signal.

$$d \in D^n : d \to w_1 \cdot f_1(s) \otimes w_2 \cdot f_2(s) \otimes \cdots \otimes w_n \cdot f_n(s) \tag{1}$$

where f_i are heuristic signal transforms and w_i corresponding weighting functions. Usually during the tests of newly developped interpretation software the results are calculated for a limited database (learning set), verified, and used for corrections of computation coefficients.

2.2. MATCHING PURSUIT

The procedure compares the current record with a set of dictionary functions $g_{\gamma 0} \in \mathbf{S}$ known beforehand. Amplitude and scale normalization are used to suppress basic extracardiac variability sources. The matching coefficients R^n estimate how far the signal f could be explained by a given pattern. The decomposition procedure starts with the best fitted pattern

$$f = \left\langle f, g_{\gamma 0} \right\rangle \cdot g_{\gamma 0} + R^1 \cdot f \tag{2}$$

and the residual signal R is recursively processed up to the desired number of coefficients n:

$$R^i \cdot f = \left\langle R^i \cdot f, g_{\gamma i} \right\rangle \cdot g_{\gamma i} + R^{i+1} \cdot f \tag{3}$$

The procedure yields the signal represented by a set of matching coefficients R^i over the dictionary functions $g_{\gamma i}$ and the remaining signal $R^n \cdot f$ representing all unexplained signal components:

$$f = \sum_{i=0}^{n-1} \left\langle R^i \cdot f, g_{\gamma i} \right\rangle \cdot g_{\gamma i} + R^n \cdot f \tag{4}$$

Its energy is the estimate of matching quality (or dictionary adequacy). The construction of appropriate dictionary resulting in explanation of principal diagnostic features with use of minimum number of coefficients is a very challenging, but still unresolved issue.

2.3. EXTENSION OF COMPRESSION ALGORITHMS

ECG data compression techniques do not have a common mathematical expression and are usually classified in three major categories:

- direct data compression (e.g. AZTEC, SAPA, CORTES, delta coding, approximate Ziv-Lempel etc.)
- transform coding (e.g. Karhunen-Loeve Transform, Discrete Cosine Transform, wavelets etc.)
- parameter extraction methods (e.g. linear prediction, vector quantization, neural networks etc.)

Since the expectation of maximum signal fidelity at a minimum data rate is very similar to those of signal compression, specialized data reduction algorithms may be adapted to the computation of machine ECG description. Main assumption made during such adaptation is no necessity to accurate data reconstruction. Such approach is already commercialized for management of digital media as MPEG-7 standard. However, in case of medical record the diagnostic meaning of the signal have to be preserved with maximum care. Therefore, the unchanged content is completed by a preceding data fingerprint containing the description of most representative features from the user's viewpoint. In case of electrocardiograms these features includes intermediate data for the diagnostic parameters.

2.4. SYNTACTIC DESCRIPTION OF ELECTROCARDIOGRAM

The syntactic description of the ECG consists of words composed of symbols x_i belonging to the finite set called alphabet.

$$V = \{x_1 \cdots x_n\} \tag{5}$$

The alphabet includes tokens referring to the waveform shapes expected in the signal as well as the features of signal derived automatically. Tokens are grouped to symbols using a grammar $G_A = (V_N, V_T, S_{out}, S_{in})$ accordingly to its syntactic and semantic rules.

$$X \to a, \quad for\ X \in V_N \quad and\ a \in V_N \cup V_T \tag{6}$$

$$\begin{aligned} Y_1 &= f_1(X_{11}, \cdots, X_{1n1}, Y_1, \cdots, Y_n) \\ &\vdots \\ Y_n &= f_n(X_{n1}, \cdots, X_{nnn}, Y_1, \cdots, Y_n \end{aligned} \tag{7}$$

where X_{ij} are symbol attributes and f_i stand for semantic procedures. Definition of semantic rules is based on the cardiologist's reasoning and thus high adequacy of signal representation can be well combined with algorithms flexibility [7].

3. AUTOMATIC UNDERSTANDING OF THE ECG CONTENTS

The term 'automatic understanding' [9, 10] is proposed for all the non-assisted procedures aiming at deriving the optimal description of ECG contents. The procedures do not attempt to interpret the diagnostic data and thus the interpretation is made by the expert or appropriate software. However, the automatic understanding is based on medical aspect of the signal what involves a substitute of the interpretation intelligence to be incorporated into the software. Taking into account that such software is intended to a wearable computer of limited resources, the interpretation methodology should be properly defined by cardiologists.

The definition of interpretation methodology needs the investigation of diagnostic procedures with use of direct and indirect methods. Direct methods assume that the expert can willingly express his opinion. From a set of available methods we used: standards and recommendations from cardiology associations as well as personal inquiries. Indirect methods base on non-standard investigation techniques and assume no cardiologist's opinion is explicitly expressed. Two methods were used in our research: analysis of the experts scanpaths acquired during the records interpretation and tracing of the expert's corrections made to automated ECG interpretation. In order to have the data amount representative to the cardiologist reasoning and sufficient for statistic-based conclusions the experiment is planned for years, and the results presented here shall be completed in the future.

4. RESULTS

From the viewpoint of automatic ECG understanding, the positive outcome is manifested through the synergy of methods performance known as a cognitive resonance. Such synergy was found in two intersection cases of description methods and interpretation procedures presented in figure 3:

- the automatic waves segmentation combined with the scanpath analysis results in an adaptive discrete signal representation [2]
- the syntactic description combined with expert's correction tracing provides an exhaustive representation of principal waveform features.

	cardiology standards and recommendations	personal inquiries	experts scanpaths analysis	experts corrections tracing
automatic segmentation of waves				
matching pursuit				
extension of compression algorithms				
syntactic description of electrocardiogram				

Fig 3. Areas of automatic understanding of the electrocardiogram

It is worth a notice that both these cases lead to different optimal ECG description formats on subsequent stages of the interpretation process. First of the resonance point was already tested in a prototype application of a microcontroller-based cardiomonitor with non-uniform sampling [1] and was found an interesting alternative to the compression of ECG signal (Fig. 4). Furthermore, our result does not exclude other points of cognitive resonance in course of further investigation.

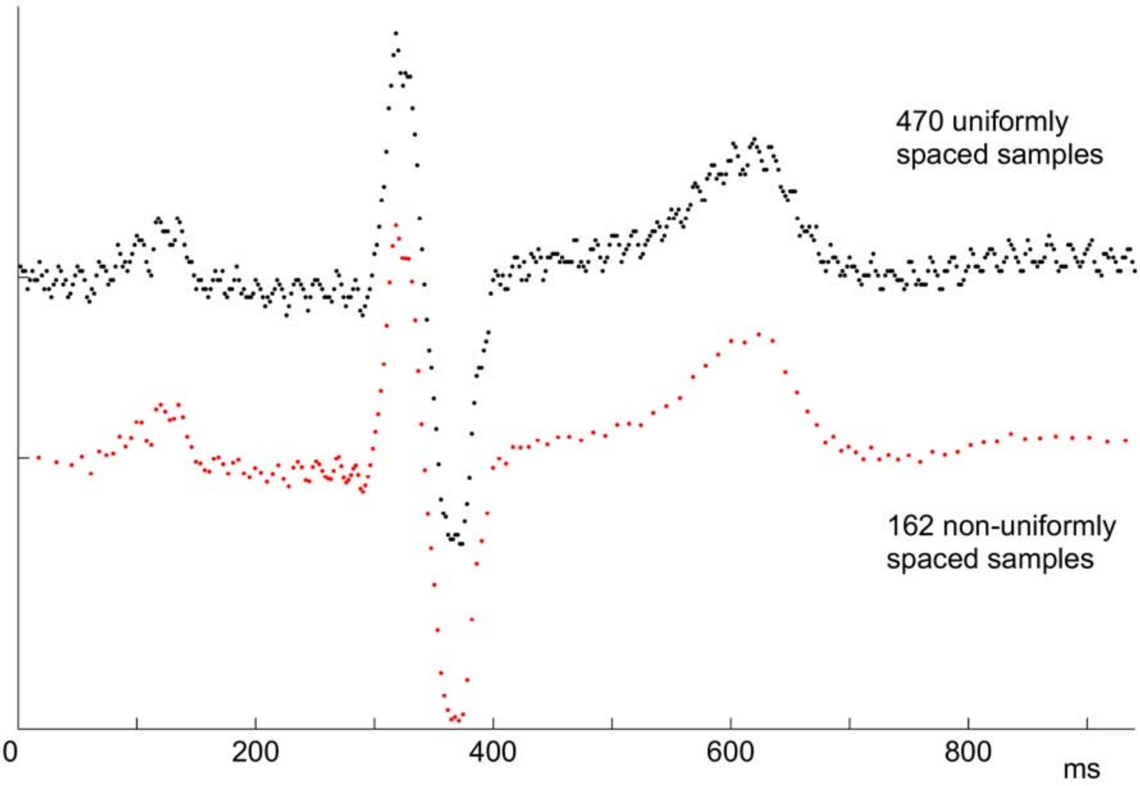

Fig. 4. Example of non-uniformly sampled heartbeat compared to a regular discrete representation

5. CONCLUSION

The distributed interpretation intelligence applied to a wearable cardiomonitor has several advantages over a conventional recorder. Most of them result from the optimal data set transmitted from the remote recorder to the surveillance center. This data is pre-interpreted what means the suppression of most important extracardiac information and extraction of diagnostically most important signal features. The actual interpretation is performed under the supervision of an expert alerted in case of any abnormal recording.

6. ACKNOWLEDGMENT

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