Model Based Signal Characterisation for Long-Term Personal Monitoring

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Abstract

This paper presents a prototype of a portable unit for automatic on-line monitoring and analysis of the ECG, used as a pilot study of a wider, advanced project, whose rational has the following guidelines. According to the largely recognised trend toward the achievement of a tight physician to patient co-operation, this project has been conceived both to alleviate physician from visits due to false alarms and to allow the educated patient to report accurately his symptoms. Such a piece of equipment should perform accurate analysis of on-line signals and generate dependable alarms. It is based on a pocket-size (PC-104) computer, running full Windows-95 OS, and three subsystems carried out in our lab (A/D converter, LCD with control buttons, smart card for system personalization). This choice has the unique advantage of compatibility with available algorithms and portability of standard applications. Moreover the number of active system channels will be easy to expand or reduce according to patient needs.[3]

1. Introduction

Development of devices for **personal** monitoring has gained a new momentum because of various factors, like: availability of resources, demand of home care providers, increased costs of in-hospital assistance, international trend [1].

As far as the design approach is concerned, a trade off has to be defined between conceiving low cost general purpose systems, only partially fitting to patient's needs, and an opposite proposal based on highly flexible systems, able of working according to spec's generated by the patient himself.

Such a system, at a pilot stage level, has been designed and carried out aimed at help persons in monitoring, perceiving and possibly managing their own health conditions, under the responsibility and supervision of the practitioner [1,2]. A first version has implemented the stand alone ECG monitor only, so to evaluate the original design features before extending system's potentiality (let's use the name actually given to the full system: ***compass, co-operating mobile patient assistance** and surveillance system)*

2. System overview

Compass has been developed according to the following rational pathway.

Deep and extended changes are going to characterise health systems organisation in Europe, North America, and some of the countries of Pacific area, along common directions [2]. One of these will be the ***managed care*** approach that has some implications on the augmented role of the practitioners, as physicians of the metropolitan area, and of the patient as well.

Compass is build around a pocket-size (PC-104-) computer, running full Windows-95 OS. After a convenient initialisation that will be part of the routine duties of the service provider the patient's data will be stored on a smart card (24C16 EEPROM-PIC16F84) together with the typical templates of each individual patient.

The card starts Compass, uploads the initialisation data, so that the process can begin.

The application software has a concurrent multi-thread general structure, that implements the real time signal processing algorithms.

The detection procedures are based on the discrimination of signal components versus background operated by an original non linear filter; analysis procedure includes a model based parameter extraction that captures **patient signature.** Interpretation of signs has been so far implemented with a simple context aware technique, carried out by a mixed sequential combinatorial network. An LCD driven by some push-buttons implements patient-machine interaction. Finally a smart-card plays a triple role: stores the patient-specific parameters of the model generating the templates, stores essential clinical record data and is the system physical key. A co-operation with practitioners and hospital clinicians has started, aimed at providing a background experience and evaluating main problems of the last system's feature, the communication through a network of metropolitan services, not yet available.

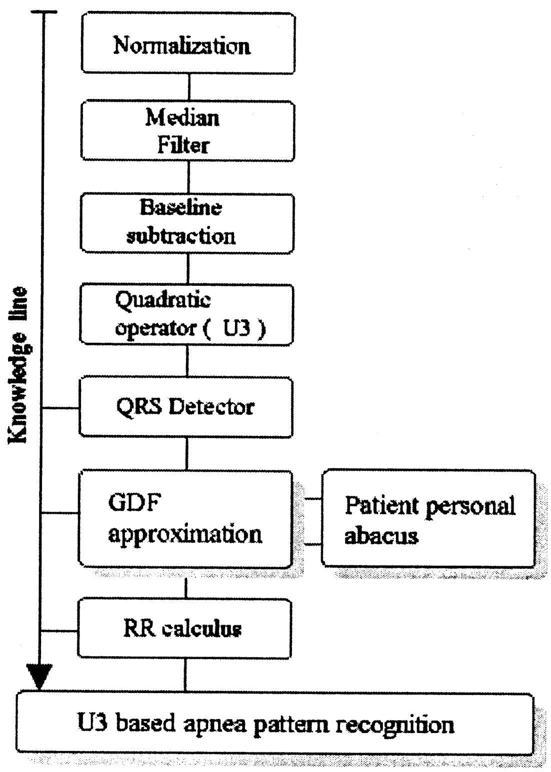


Figure 1. Simplified COMPASS flowchart

3. Algorithms

3.1. Preprocessing

Continuous flow of ECG samples, packed in 10 second records, is calibrated according to analog channel gain and scaled in the interval 0..1.

A double moving median filter is then used to reduce low frequency noise, particularly the baseline shift, according to:

$$\mathrm{Out}_i = \mathrm{median}\left(\mathrm{ECG}_{i-\frac{n-1}{2}}, \ldots \mathrm{ECG}_i, \ldots, \mathrm{ECG}_{i+\frac{n-1}{2}} \right)$$

where 2n+1 is the filter's moving window width.

Residuals are then calculated :

$RES_i = ECG_i - Out_i$

Iterating on RES, we obtain a vector RESm, and then:

$ECGNi = ECGi - (Outi + RESm_i)$

Choosing an appropriate n the ECGN vector will include a filtered ECG signal ready to be processed by the detection algorithms. Figure 2 shows the result of such a filtering procedure on the record of an ischemic attack.

3.2. The non linear operator

In order to enhance the wanted signal features a non linear operator was introduced by exploiting the curve-length concept. In this phase we will use this operator in order to detect QRS complexes. Fig 3 shows that the lengths L1 and L2 characterize the shape of the curves, given a certain time interval. This principle can be applied to detect the wave fronts that characterizes the beginning and the end of an episode

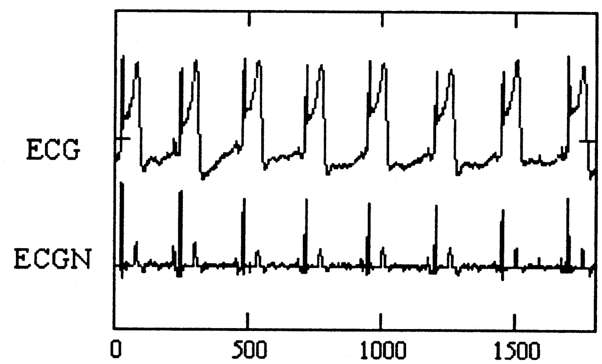


Figure 2. Double median filter effect (see equation)

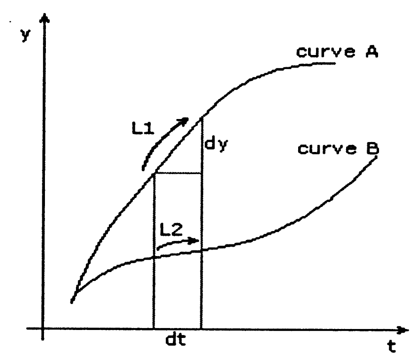


Figure 3. The curve length concept

In the discrete time domain we can approximate the arc length relative to the i-th sample with the chord length, obtaining:

$$L_i := Dt \cdot \sum_{w} \sqrt{1 + \frac{Dy^2}{Dt^2}}$$

Dt is the sampling interval, Dy represents the i-th increment and w is a rough estimate of the duration of the episode (or waveform) to detect. Now, being Dt a constant, taking the square to further enhance the edges (i.e. the duration of the line referred to time) we obtain:

$$L = \sum_{w} Dy^2 \quad \text{or even}$$

$$L_i = \sum_{k=i-n}^{i+n} \Delta\varphi_k^2$$

if $\Delta\varphi$ is a finite difference operator and $w=2n+1$ the filter window (i.e. the estimated duration of the wave to be optimally discriminated and detected), we've

$$L_n = \sum_{k=0}^{2n} (y_k - y_{k-2})^2 \quad \text{initial condition}$$

recursive equation

$$L_i = L_{i-1} - (y_{i-n-2} - y_{i-n})^2 + (y - y_{i+n})^2$$

The figures 4, 5 show the input/output signals in reference conditions and during an ischemic attack respectively: Even in such critical cases, in spite of dramatic signal changes, the QRS's are still detectable with the same algorithm used before episodes.

3.3. ECG modeling by gamma density function (GDF)

From a technical point of view it would be preferable to avoid the very subjective operation of extraction empirical parameters and to use models, when available or transforms for enhancing wanted signal features.

Our scheme, since global interpretative models are missing in our application domain, consists in a waveform statistical shape modeling. During an out-patient learning session, patient's ECG is analyzed in order to define a range of the GDF parameters that allows the wave synthesis within a predetermined error, according to an optimization technique. The GDF model allows to derive global parameters (i.e. the parameters of the best fitting gamma distribution) to represent the ECG waveforms (Fig. 6, 7).

The general expression of ***gamma distribution*** is:

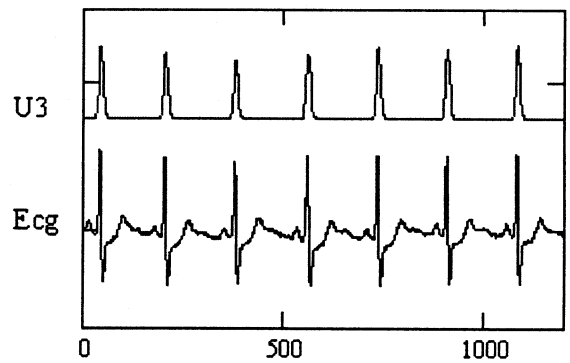
$$\gamma(x,\alpha,\beta,t_0) = \left(\frac{x-t_0}{\beta}\right)^{\alpha-1} \frac{\exp\left(-\dfrac{x-t_0}{\beta}\right)}{\beta\cdot\Gamma(\alpha)}$$

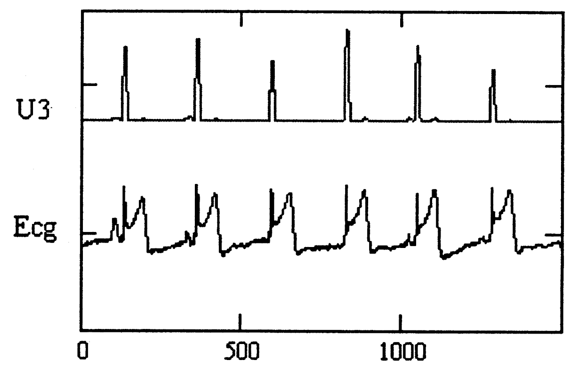
where the parameters α, β regulate shape and scale respectively. The above integral converges for $x>0$.

The personal abacus compressed in a couple of α and β for each wave is stored on the smart card (Fig. 7, see paragr. 2).

In this way different patients will use the same hardware modules, but the analysis is strongly personalized through their individual cards; that's what we call **disposable** software.

Reduction of parameters space dimension is only one of the advantages we've found with this interpolating technique. Further useful features can be reported about the better definition of time intervals (RR, QT) made through the gamma waves, less affected by local noise.





Figures 4 (reference conditions), and 5 (ischemic attack).

4. Context aware computing

Figure 1 shows a line linking the various functions, called *knowledge path*. It suggests the relevance of AI methods to supplement procedural algorithms, in order to embed domain knowledge, that is patient specific contextual data. The alarm generating function has been based on a combinatorial network, whose inputs were derived from parameters supplied by the basic procedure. Some complex *strobe* signal has been evaluated by ***logit*** method, while events sensitive to context in a quantitative way (PVC per hour, trends, etc) have been implemented by sequential elements.

5. Validation

A complete validation of COMPASS requires many full studies on its own. We started testing it separating various functions:

Basic detection algorithms have been tested during the CinC competitions,. They obtained with a single attempt the score 27/30, in the Challenge 2000, and were classified within the top score group.

The 2001 Challenge at the moment is not over, but we have been in leading position, again with only one attempt, for several weeks. An archive at Stanford collection of 299 persons, 166 affected by coronary stenosis, were analysed with the alarm procedure and gave a ROC curve showed in figure 8. In minmax condition sensitivity of about 0.8 and specificity 0.9.

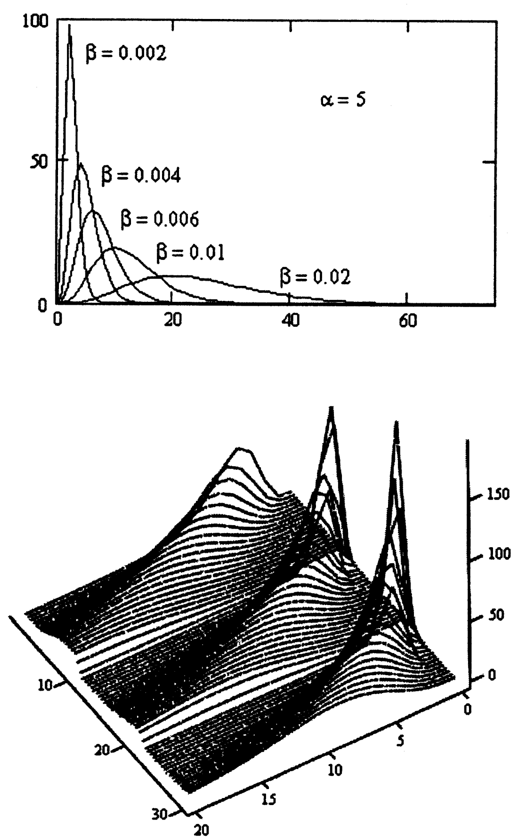


Figure 6,7. Gamma waveforms

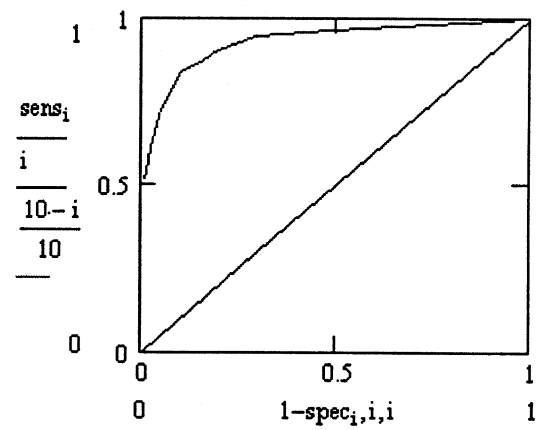


Figure 8. ROC curve

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