# Internet-based, GPRS, Long-term ECG Monitoring and Non-linear Heart-rate Analysis for Cardiovascular Telemedicine Management

S Khoór[1], J Nieberl[2], K Fügedi[1], E Kail[2]

Szent István Hospital[1], Bion Ltd[2], Budapest, Hungary

## Abstract

*A portable GSM ECG with GPRS communication was developed with an internet database for the on/off-line analysis of large amount of ambulatory ECG (www.bion.hu). 3 studies were performed determining the role of nonlinear heart rate dynamicity in the separation of various disease groups (sudden cardiac death in CHF and in post-infarction (post-MI) patients, malignant ventricular rhythm disturbances in post-MI groups. The Haar wavelet analysis (wavelet SD by scale parameters) showed a good separation in the 3-5 scale range. The multivariate discriminant models with input values of $\alpha_1$, $\alpha_2$, $\beta$ and the approximate entropy showed a good separation (Wilks' statistics: $p<0.001$) of the patients' groups. The frequent, internet based ECG monitoring would be help in the individual cardiovascular risk management.*

## 1. Introduction

The individual cardiovascular risk would be calculated by various methods, the aim of our study was to predict the outcome by nonlinear beat-to-beat long term ambulatory ECG data analysis. In this preliminary study the authors follow their works in the telemedicine field with wireless ECG [1,2]. Our telemedicine information system is called originally CyberECG, but the translated Hungarian name, "HeartSpy" better represents one of the most important feature, namely the online monitoring of the extended length (days or weeks) ambulatory ECG via the internet. Apart of this, the offline nonlinear beat-to-beat analysis is served for the patient's risk clusterization, which determines the telemedicine managing strategy. Different nonlinear methods – multiresolution wavelet- [3,4], spectral-, [5,6] Poincaré plot- [7,8], power-law-scaling- [9], detrended fluctuation- [4,10,11] and approximate entropy-analysis [12-14] – were used for heart rate time-series analysis and morbidity/mortality prediction [15,16]. Some special patient groups, the chronic heart failure (CHF) and postinfarction (post-MI) patients with or without sudden cardiac death (SCD), post-MI patients with or without malignant ventricular rhythm events, were chosen in the present study. Multivariate discriminant analysis was performed with input values of these nonlinear parameters, and the mortality or other primary events were the output values. The patients were clusterized by this way to low or high risk groups, and the medical management (e.g., frequency of long-term ECG monitoring) is planned due to this decision.

## 2. Method

### 2.1. Wireless ECG information system

Figure 1. shows the whole system. The portable, pocket-sized measure device communicates by a GSM-GPRS route. Its operation could be changed "Over The Air" (OTA) from one to twelve channel ECG. The high resolution (24 bit, 0.5 ms sampling rate) full digital ECG recorder sends the compressed data via wireless network. The size of each ECG pocket is 120 byte, the averaged communication bandwidth between 56 and 118kbit/s.

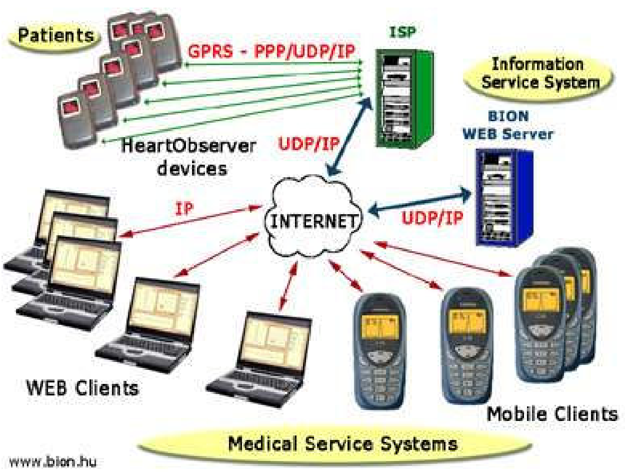


Figure 1. The CyberECG System.

The WEB server contains the ECG Knowledge- and Data-base, and broadcasts the ECGs to the medical users. The medical staff could real-time, continuously monitor the patients with PC, or mobile phone.

## 2.2. Calculations

**Haar wavelet analysis**

The multiresolution wavelet analysis (MWA) is based on the transforming the discrete time sequence of R-R intervals into a space of wavelet coefficients. The method proposed Thurner and Ashkenazy [3,4] with the Haar wavelet was used. The coefficients are calculated by:

$W_{m,n}(s) = 2^{-m/2} {}_{i=0}\Sigma^{M-1} \tau_i \psi(2^{-m}i-n)$

where the scale variable $m$ and the translation variable $n$ are nonnegative integers, and $M$ represents the total number of R-R intervals analyzed. The wavelet-coefficient standard deviation reflects the variability of the signal, as a function of scale:

$\sigma_{wav}(m) = [1/(N-1)\ {}_{n=0}\Sigma^{N-1}(W_{m,n}(s) - W_{m,n}(s)))^2]^{1/2}$

where $N$ is the number of wavelet coefficients at a given scale $m$.

**Poincaré plot analysis**

The quantitative analysis is based on fitting an ellipse to the Poincaré ($R\text{-}R_0$ vs. $R\text{-}R_{+1}$) plot (Figure 2.).

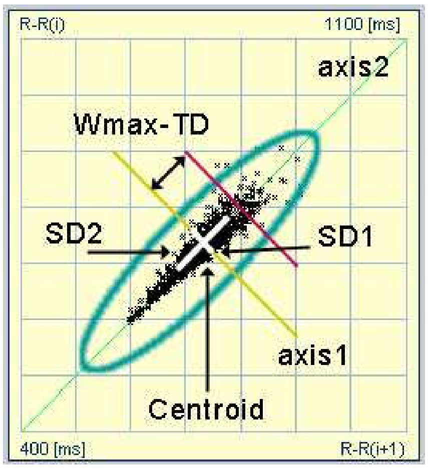


Figure 2. The Poincaré ($R\text{-}R_0$ vs. $R\text{-}R_{+1}$) plot.

First the centroid was determined (mean $R\text{-}R_0$ / $R\text{-}R_{+1}$), with the two axis (longitudinal = axis_2, perpendicular = axis_1). STD-1 represents the continuous long-term, STD-2 the instantaneous RR-interval variability calculated as the standard deviation of data points passes through that axis direction. Wmax-TD is the distance between the centroid and the averaged maximum of instantaneous interval variability.

**Power-law-scaling Analysis**

In our studies an autoregressive model (model order: 20) was used to estimate the power spectrum densities. The heart rate time series were partitioned into 512 R-R interval segments. The point power spectrum was logarithmically smoothed in the frequency domain and the power integrated into bins spaced 0.0167 log (Hz) apart. A robust line-fitting algorithm of log (power) on log (frequency) was applied to the power spectrum between $10^{-4}$ and $10^{-2}$ Hz and the slope of this line ($\beta$) was calculated.

**Detrended Fluctuation Analysis (DFA)**

The slope of the line relating log F(n) to log n determines the scaling exponent (self-similarity parameter = $\alpha$ ) was calculated with detrended fluctuation analysis (DFA) ( for short-term (<11 beats)= $\alpha_1$ and for long term= $\alpha_2$). The integrated NN time series are divided into windows of equal length, n. In each window of length n, a least-squares line is fitted to the data. The y coordinates of the straight line segments are denoted by yn(k). The integrated time series were detrended by subtracting the local trend, yn(k), in each window. The root-mean-square fluctuation of this integrated and detrended series is calculated. The computation is repeated over all time scales (window sizes) to obtain the relationship between F (n) and the window size n. A linear relationship on a log-log plot indicates the presence of scaling. The DFA calculations were applied to the entire recording from averaged segments of 6000 R-R intervals.

**Approximate Entropy**

The approximate entropy (ApEn) quantifies the unpredictability of fluctuations in a time series. A time series containing many repetitive patterns has a relatively small ApEn, a less predictable (i.e., more complex) process has a higher ApEn. ApEn(SN,m,r) = ln (Cm (r)/ Cm+1 (r)), where SN, the sequence, m specifies the pattern length, r defines the criterion of similarity, Cm (r) is the quantity of the fraction of patterns of length m that resemble the pattern of the same length that begins at interval i. The ApEn was calculated for 4000 heart rate data point. Fixed values for two input parameters, m and r must chosen to compute the ApEn of the sequence, ApEn (m,r,N), where m, specifies the pattern length (m=2), and r defines the criterion of similarity (r = 20% of the standard deviation of the data sets). The fast algorithm of Fusheng [17] was used.

**Multivariate discriminant analysis (MDA)**

The SPSS statistical package was used for MDA.

The discriminant score was calculated based on the unstandardized discriminant function coefficients. The canonical correlation measures the degree of association between the discriminant scores and the groups. The Wilks' lambda is the ratio of the within-groups sum of squares to the total sum of squares, and this parameter was used for the stepwise selection of input values. TheWilks' lambda was calculated for significance of the discriminant functions.

## 3. Study population

### 3.1. Study-1.

The multiwavelet analysis (MWA) based on the data of 27 CHD patients with SCD (CHD_SCD+) and 27 without it (CHD_SCD-), selected from a 168 CHF patients population monitored for 24 hours in every four weeks for six months. The inclusion criteria were: telemedicine ambulatory ECG (ta-ECG) recordings at least 4 weeks before the SCD, absence of acute myocardial infarction in the previous 1 year. SCD was defined as death occurring within 15 minutes of a change in symptoms or during sleep. Clinical features of the two groups: male/female (Group-A: 14/13, Group-B 14/13; age: 62.4+-7, 59.7+-6; CAD: 22, 21; other cause: 5, 6; NYHA II. class: 18, 17; NYHA III. Class 9, 10; EF: 36.2+-6, 36.9+-5, respectively).

### 3.2. Study-2.

In the second study two different multivariate (3 groups) discriminant models have been developed for the high risk patients: SCD in CHF (Group-1, N=33), no SCD in CHF (Group-2, N=52); SCD in postinfarction (post-MI) patients (Group-3, N=29), no SCD in post-MI (Group-4, N=50) and matched healthy control (Group-5, N=50 vs. CHF groups, Group-6, N=50 vs. post-MI groups). There were no differences in the prevalence of hypertension, diabetes, ejection fraction, the use of beta blockers and/or ACE inhibitors. The frequency of ta-ECG was 24 hour weekly and lasted for 12 months.

### 3.2. Study-3.

The study population consists of 78 postinfarction patients with ejection fraction <35%, who had more than 6000 ventricular premature beats during 48 hour ECG registrations. During the 12 months, 4-weekly telemedicine observation 19 of them had sustained ventricular tachycardia (VT) or fibrillation (VF) (Group-A), 59 had not (Group-B). The normal-to-normal beat (NNT), the interectopic- (IIT), and the coupling interval (CIT) were determined from the last 24 hour registration before the arrhythmic event. The input nonlinear parameters were determined from the entire data set for NNT, and from the 6000 IIT and CIT series.

## 4. Results

### 4.1. Study-1.

The phase-space of the wavelet-coefficient standard deviation and the scale parameters (Figure 3.) showed an excellent separation in the scale-range of 4-6 between the groups: in that region, the average scaling exponents was 0.14+-0.04 for Group-A, and 1.22+-0.27 for Group-B (p<0.001).

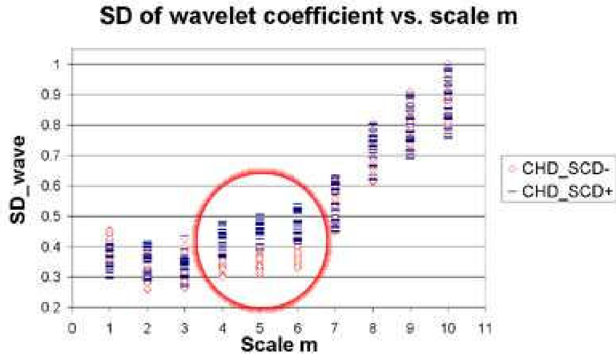


Figure 3. Standard deviation of wavelet coefficient vs. scale m.

### 4.2. Study-2.

The input values were the SD-1, SD-2 and Wmax-TD from the Poincaré plot; α1 and α2, calculated with DFA, β, the slope of a line fit by a least-squares criterion to a log-log plot of power versus frequency for frequencies between 0.001 and 0.1 Hz and the ApEn. Table 1. represents the descriptive statistics of the parameters in the CHF groups.

Table 1. Descriptive statistics of parameters of CHF groups.

| | Control | CHF-SCD+ | CHF-SCD- |
|---|---|---|---|
| SD-1 | 21.4 +-8.60 | 14.30 +-7.10 | 18.50 +-6.70 |
| WmaxTD | 83.9 +-47.0 | 34.90 +-11.4 | 93.40 +-23.5 |
| $\alpha_1$ | 1.07 +-0.40 | 0.84 +-0.13 | 0.97 +-0.18 |
| $\alpha_2$ | 1.02 +-0.30 | 0.72 +-0.13 | 0.89 +-0.20 |
| Β | -1.30 +-0.50 | -1.74 +-1.10 | -1.70 +-0.90 |
| ApEn | 1.04 +-0.12 | 0.79 +-0.09 | 0.89 +-0.12 |

A three-group discriminant analysis was performed with two function (F-1 and F-2). For F-1 the eigenvalue was 47.98, the percent of variance 99.58, the canonical correlation 0.98, the Wilks' lambda 0.017 , chi-square 601.09, p< 0.00001, for F-2 the values are 0.203, 0.42, 0.411, 0.83, 27.26, 0,0001, respectively.

Table 2. represents the descriptive statistics of the parameters in the post-MI groups.

Table 2. Parameters of post-MI groups.

| | Control | Post-MI-SCD+ | Post-MI-SCD- |
|---|---|---|---|
| SD-1 | 19.2 +-7.20 | 13.92 +-4.20 | 17.40 +-2.10 |
| WmaxTD | 81.6 +-11.3 | 51.11 +-10.8 | 69.40 +-14.3 |
| $\alpha_1$ | 1.05 +-0.36 | 1.8 +-0.10 | 1.16 +-0.11 |
| $\alpha_2$ | 1.01 +-0.26 | 0.67 +-0.16 | 0.84 +-0.23 |
| Β | -1.24 +-0.33 | -1.62 +-2.40 | -1.41 +-1.95 |
| ApEn | 0.99 +-0.17 | 0.85 +-0.19 | 0.96 +-0.21 |

For the post-MI groups the statistical parameters of F-1: the eigenvalue was 124.35, the percent of variance 97.84, the canonical correlation 0.996, the Wilks' lambda

0.021 , chi-square 778.35, $p< 0.00001$, for F-2 the values are 2.75, 2.16, 0.856, 0.266, 167.22, 0,0001, respectively.

## 4.3. Study-3.

The same six nonlinear variables of NNT, IIT and CIT were used in the multivariate discriminant analysis. After the stepwise selection, 6 parameters remained from the 18: $x_1 = \alpha_1$-NNT, $x_2 = \alpha_1$-IIT, $x_3 = \alpha_1$-CIT, $x_4$= WmaxTD-IIT, $x_5$ = ApEn-IIT $x_6$ = ApEn-CIT.

The results of the two-groups discriminant model: the eigenvalue was 91.47, the canonical correlation 0.994, the Wilks' lambda 0.0108 , chi-square 332.726, $p< 0.00001$.

# 5. Conclusions

Some nonlinear heart rate dynamicity measurement was performed repeating the works of other authors. The results are our presented preliminary study is using in our telemedicine wireless ECG system for a year. The patients are categorized into various disease groups (or to healthy) with the calculation of discriminant score determined by the multivariate models related to their clinical feature (e.g. pts after myocardial infarction, with chronic heart failure, or rhythm disturbances). Using these scores as predictor values, the telemedicine ECG management would be designed. The worsening indicator parameters indicate immediate change of patient management (re-checking the clinical signs and symptoms, change of therapy, hospital admission). In the case of borderline decision situation (mild change of the indicator values) the ambulatory registration will extend for longer time or repeat more frequently.

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Address for correspondence.

Name. Sándor Khoór MD PhD
Full postal address. Szt István Hospital, Nagyvárad tér 1, Budapest, Hungary, H-1111.
E-mail address (optional). skhoor@bion.hu