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Computers in Biology and Medicine 34 (2004) 551–560

Computers in Biology and Medicine

http://www.intl.elsevierhealth.com/journals/cobm

Generation of digital time database from paper ECG records and Fourier transform-based analysis for disease identification

Sucharita Mitra[a,*], M. Mitra[b], B.B. Chaudhuri[a]

[a] *Computer Vision and Pattern Recognition Unit, Indian Statistical Institute, 203, B.T. Road, Kolkata 700108, India*
[b] *Department of Applied Physics, University College of Technology, 92 APC Road, Kolkata 700009, India*

Received 17 March 2003; accepted 11 August 2003

Abstract

ECG signals recorded on paper are transferred to the digital time database with the help of an automated data extraction system developed here.

A flatbed scanner is used to form an image database of each 12-lead ECG signal. Those images are then fed into a Pentium PC having a system to extract pixel-to-pixel co-ordinate information to form a raw database with the help of some image processing techniques. These raw data are then ported to the regeneration domain of the system to check the captured pattern with the original wave shape. The sampling period of each ECG signal is computed after detection of QRS complex. Finally, discrete Fourier transform of the generated database is performed to observe the frequency response properties of every ECG signal. Some interesting amplitude properties of monopolar chest lead V4 and V6 are noticed which are stated.

Keywords: Electrocardiogram; Database; QRS complex; DFT; Frequency response

1. Introduction

In the age of Information Technology, creation of a database is essential for storing, retrieving or processing of information regarding any field. A purely computerized data extraction and processing system is much more acceptable today because of its wider application potential. In this paper, we concentrate on developing a totally computer-based data extraction and processing system of 12-lead ECG signals.

ECG is only a laboratory test and is not a "sine qua non" of heart disease diagnosis. A patient with an organic heart disorder may have a normal ECG while an absolutely normal person may have

* Corresponding author. 27, Rishi Arabinda Sarani, Kolkata 700090, WB, India.
E-mail addresses: susa68@hotmail.com (S. Mitra), m_mitra@vsnl.net (M. Mitra), bbc@isical.ac.in (B.B. Chaudhuri).

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doi:10.1016/j.compbiomed.2003.08.001

nonspecific electrocardiographic abnormalities. Therefore, further analysis of ECG records should be carried out to obtain a more specific observation and detection of cardiac abnormalities.

Some systems were developed which can transfer wave data recorded on paper to a digital time data [4–6,13].

An instrumentation scheme using a computer aided design and drafting (Auto CAD) application package is already being used to generate ECG database. Here, a single-channel strip chart recorder and a digitizer with a tablet attached to the RS 422/432 port of the computer are used as an input device. The digital plotter/printer–plotter was used as an output device [2].

This CAD based data acquisition system was used to study the polar phase response property of monopolar chest-leads (V_1–V_6) ECG voltages. The spin harmonic constituents of ECG voltages are evaluated at each harmonic plane and the polar phase responses are studied at each plane [3].

In conventional ECG analysis, the general tendency is to extract time plane features from these signals. But time plane ECG wave may be corrupted by different types of noises e.g., 50 Hz power line interference, Electromyographic (EMG) signal, baseline wandering due to respiration, electro-surgical noise, abrupt baseline shift, etc. Spectral analysis of ECG wave is particularly helpful in noise reduction, data compression and feature extraction for disease identification.

The frequency characteristic of each segment of ECG signal was computed via fast Fourier transform (FFT) to identify the cardiac abnormalities [1]. It demands that the accuracy, reliability and consistency of the algorithm verified. The diagnostic performance of the peak value of the Fourier spectrum as a classifier for subjects prone to ventricular arrhythmia showed an improvement over the use of the extreme count method [16]. Using a discrete-Fourier transform (DFT) signal-averaging variant and a series of mathematical transformations, the computer-expert system analyzed signals in the 0.1–50-Hz range. The system identified abnormalities by comparing results with a patient database culled from predicate research [17]. Both DFT and discrete harmonic wavelet transform (DHWT) are used for frequency and time–frequency spectral analysis of heart rate variability as a diagnostic marker of the sleep apnoea syndrome [18]. The selective discrete Fourier transform (DFT) Algorithm [SDA] method for the calculation and display of time–frequency distribution has been developed and validated. For each time and frequency, the algorithm selects the shortest required trace length and calculates the corresponding spectral component by means of DFT. This approach can be extended to any cardiovascular-related signal and provides time-dependent power spectra which are intuitively easy to consider, due to their close relation to the classical spectral analysis approach. The optimal parameters of the SDA for cardiovascular-like signals were chosen [19]. Time and frequency domain analysis was carried out for the detection of late potentials to identify ventricular tachycardia (VT) and sudden cardiac death [20]. Frequency analysis using the maximum entropy method (MEM) based on an autoregressive (AR) model was used for identification of patients with sustained ventricular tachycardia [21]. Time–frequency analysis of ECG data have also been carried out in [7–9,14].

In this study, a high-resolution flatbed scanner is used to capture the image of each ECG signal recorded on a single-channel chart recorder. These images are then fed to a computer-based software system developed by us with the help of some image processing techniques to generate the raw database in ASCII format. These data are then sorted and ported to the regeneration domain of the system to check the captured pattern with the original wave form. Another algorithm is developed to detect the QRS and sampling period of each signal. At present the sampling rate is confined to $\sim$ 1181 samples per second on an average. With the help of the DFT domain of the algorithm both

the frequency and phase response property of each ECG signal can be obtained. In this paper some interesting amplitude properties of lead V4 and V6 are reported. Statistical analyses have also been carried out.

2. Proposed method

A flatbed scanner (HP ScanJet 4C model) of high resolution (1200 dpi) and 256 gray tone spectral resolution is used to scan ECG paper records and those images of ECG signals are fed into a personal computer (PC) having a system for extracting pixel-to-pixel co-ordinate information. For this purpose the following steps were involved:

2.1. Binarization of ECG images

In this process, a gray tone image was converted into two tones or binary image after selecting a suitable threshold with the help of histogram analysis.

2.2. Background separation

A suitable threshold selection after histogram analysis can mostly remove the background, e.g. gridlines of ECG papers. However, some dotted portions may exist in few cases, for which Runlength Smearing algorithm [12] was used in a different manner. Two consecutive runs of *zero* are smeared when they are separated by *ones* of length less than a pre-defined threshold.

2.3. Thinning of the input signal

A thinning algorithm was developed to obtain the skeleton of the ECG signal [10] particularly for avoiding the unnecessary data repetition in the data set of the database.

2.4. Raw data extraction

In this step, the co-ordinate of each black pixel was extracted and then the values were calibrated according to the co-ordinate system of the chart. To standardize the ECG database, this calibration part is essential. One of the important parameters of ECG signal is the patient's heart rate. Hence, we also included the heart rate of each patient in each data file of the database.

2.5. Data sorting and re-generation of the ECG signal

The raw data generated from the image were arranged according to their ordinate value. But normally, the graphical data are arranged according to their abscissa value. A sorting routine is developed to sort the raw data according to their value of abscissa.

Now the sorted data are ported to the regeneration domain of the system for checking the captured pattern with the original wave shape. Figs. 1–3 show the original and regenerated ECG signals before and after thinning, respectively.

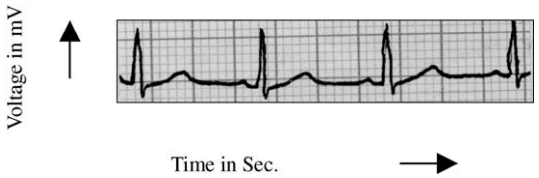

Fig. 1. Image of the original ECG signal from chart record.

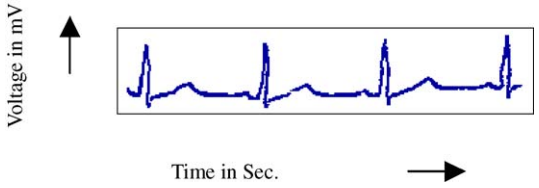

Fig. 2. Extracted ECG signal before thinning.

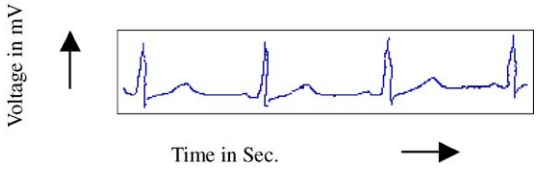

Fig. 3. Reproduced ECG signal from the extracted database after thinning.

2.6. Determination of sampling period

The sampling period, i.e., the number of samples per second was computed. The total number of samples occurring between two consecutive peaks of ECG signal was calculated.

After a thorough observation, we noticed a very sharp transition of ECG voltage from the baseline at every peak. Another module is developed for the detection of QRS to calculate the sampling period. In this module the second order derivative of the captured signal was computed using the 5-points derivative method. After squaring those derivatives, a derivative curve having a maximum area at the peak region can be obtained. A small window of considerable length was taken to detect two consecutive QRSs and hence the total samples and the distance between them were also computed. So, the sampling period can easily be calculated for each signal. We obtained an accuracy of $\sim 98.4\%$ in the detection of QRS by this method.

2.7. Discrete Fourier transform

Discrete Fourier transform of each data set was performed after obtaining the sampling period to observe both frequency and phase-response properties of every ECG signal. The algorithm was

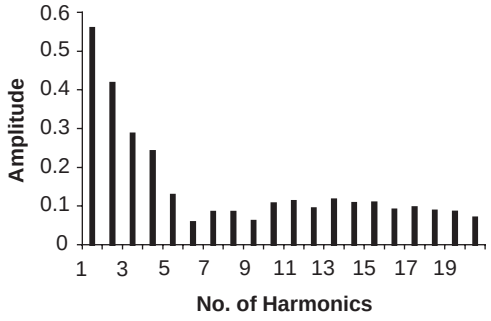

Fig. 4. Plot of harmonic amplitude vs. harmonic number for a normal subject for lead V6.

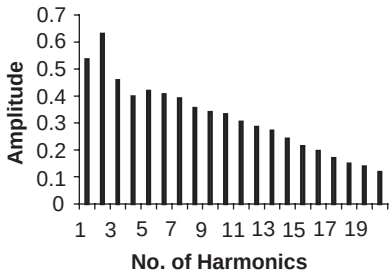

Fig. 5. Plot of harmonic amplitude vs. harmonic number for an ischemic subject.

developed according to the equation given below:

$$\mathrm{H(N}/NT) = [T/(NT)] \quad \mathrm{e}^{-\mathrm{j}2\pi nk/N},$$

where NT is the time duration and N-sample values of h(kT) which must represent exactly one complete period of the periodic function $h(t)$; n is the number/order of harmonics. All ECG signals were reproduced by inverse Fourier transform operation. Figs. 4 and 5 show the amplitude diagram for normal and ischemic patients.

3. Result

Some interesting amplitude response properties of monopolar chest lead V4 and V6 were noticed which are stated below:

The summation of first 2 harmonic vectors' $(H1 + H2)$ amplitudes (not normalized) of lead V4 for Infarction patients was nearly equal to ~ 2 or > 2, whereas for normal subjects this value was ~ 1 or < 1.

On the other hand, the summation of amplitudes of first 5 harmonic vectors $(H1+H2+\cdots+H5)$ for ischemic patients was always > 2 whereas for normal patients, the value was always < 1.85. So a threshold can be implemented for disease identification. So the decision, i.e., whether the ECG signal is normal or diseased can be made after selecting a suitable threshold.

Table 1
List of the sum of the first two harmonics

$H1+H2$	
Normal (for V4)	Infarction (for V4)
0.608963	5.620213
1.054717	4.806513
0.780408	3.319464
0.422775	2.645909
1.219696	4.41134
1.253023	1.877871
0.667245	1.794706
0.8852	2.048593
1.010489	1.92876
0.442775	3.257229

Table 2
List of the sum of the first five harmonics

$H1+H2+\cdots+H5$	$H1+H2+\cdots+H5$
Normal (for V6)	Ischemia (for V6)
1.049784	2.751346
1.342515	2.456507
1.632956	3.065879
1.337408	2.232169
1.786409	2.49857
1.250203	2.866814
0.915975	4.109885
1.469156	3.165829
1.050523	2.332163
1.539256	2.867214

Still the observation is being carried out on 20 normal and 40 diseased subjects out of which 20 patients have acute myocardial infarction and rest of the 20 patients have myocardial ischemia. Tables 1 and 2 show a portion of the amplitude sum of harmonic vectors for lead V4 and V6.

For statistical analysis, let X and Y be the average value of the summation of harmonics for diseased and normal cases following normal distribution with means $\mu 1$ and $\mu 2$, respectively. Variances for the two cases are different. So the test procedure described by Goon et al. [11], for testing the null hypothesis is needed. $H_0 : \mu 1 = \mu 2$ and there was essentially no significant difference between the summation of amplitudes of normal and diseased subjects against the alternative hypothesis.

$H_1 : \mu 1 \neq \mu 2$, and there was essentially a significant difference between the summation of amplitudes of normal and diseased subjects against the alternative hypothesis. We used the following

formula for test statistics:

$$t = (\bar{X} \pm \bar{Y})/\sqrt{(s_1^2/n_1) + (s_2^2/n_2)},$$

where the sample means for diseased and normal cases, $\bar{X}$ and $\bar{Y}$ were 2.961094 [infarction] and 0.842342 (observed) and 2.869909 [ischemia] and 1.313103 (observed). The sample variances s_1^2 and s_2^2 are 1.627834 [Infarction], 0.234694 [ischemia] and 0.0694976, 0.0737280 (with divisor 19), respectively. Therefore the observed values of the test statistics will be $t_{\text{obs}} = 7.28$ [Infarction] and 12.53 [ischemia], respectively. The tabulated values are $t_{0.01,19} = t_{0.05,19} = 2.539$ [15].

On the basis of sample observations, we reject H_0 against H_1 at both the significance levels $\alpha = 0.05$ or 0.01 as t_{obs} exceed the tabulated value in both cases. We conclude that the harmonic summation for normal and diseased subjects were statistically significantly different.

4. Discussion and conclusion

A software-based automated ECG data acquisition system was developed and using this database the amplitude response properties of ECG signals were observed.

In time plane different harmonics of ECG waves are superposed and they cannot show vector properties but in frequency plane both amplitude and phase properties of the harmonics are exposed for finding some interesting clinical and diagnostic application. This is useful for the doctors. For future application, a low-pass filter can be designed to extract the first five harmonics for disease identification.

The recent trend in ECG analysis is the development of more sophisticated data analysis and storing systems. Most of these systems are usually considered the time plane features of ECG signals. However, like many other medical diagnostic tools, electrocardiography suffers from lack of a communication standard. Different electrocardiograph manufacturers develop their own techniques for handling and transmitting data. To overcome this problem, the American College of Radiology (ACR) and the National Electrical Manufacturers Association (NEMA) recognized the emerging need for a standard method for transferring images and associated information between devices manufactured by various vendors. The American College of Radiology (ACR) and the National Electrical Manufacturers Association (NEMA) formed a joint committee in 1983 to develop a standard to

- promote communication of digital image information, regardless of device manufacturer,
- facilitate the development and expansion of picture archiving and communication systems (PACS) that can also interface with other systems of hospital information,
- allow the creation of diagnostic information databases that can be interrogated by a wide variety of devices distributed geographically [23].

The digital imaging and communications in medicine (DICOM) standard is the most widely used nowadays and defines an internationally accepted format for a number of common medical imaging methods (MR, CT, XA, US, NM) that are used for equipments from many manufacturers. Adding support for electrocardiogram (ECG) data to the DICOM standard would allow various ECG instruments and viewers manufactured by different vendors to communicate [22].

Our final goal is to upgrade our data acquisition and feature extraction system according to the DICOM standard and to include the frequency plane features of ECG signal to this DICOM standard after standardizing these features with adequate numbers of ECG data.

Summary

In this study, a high-resolution flatbed scanner is used to capture the image of each ECG signal recorded on a single-channel chart recorder. These images are then fed to a computer-based software system developed by us with the help of some image processing techniques to generate the raw database in ASCII format. These data are then sorted and ported to the regeneration domain of the system to check the captured pattern with the original wave form. Another algorithm is developed to detect the QRS and sampling period of each signal. At present the sampling rate is confined to ~ 1181 samples per second on an average. With the help of the DFT domain of the algorithm, both the frequency and phase response property of each ECG signal can be obtained. In this paper, some interesting amplitude properties of lead V4 and V6 are reported which can be used for disease identification. Statistical analyses have also been carried out which shows that the amplitude properties of normal and diseased subjects are statistically significantly different.

In time plane different harmonics of ECG waves are superposed and they cannot show vector properties but in frequency plane both amplitude and phase properties of the harmonics are exposed for some interesting clinical and diagnostic application. This is useful for the doctors. For future application, a low-pass filter can be designed to extract the first five harmonics for disease identification.

Our final goal is to upgrade our data acquisition and feature extraction system according to the DICOM standard and to include the frequency plane features of ECG signal to this DICOM standard after standardizing these features with adequate numbers of ECG data.

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Sucharita Mitra received her B.Sc. degree in Physics (Hons.) in 1995 and M.Sc. degree in Electronic Science in 1997 from the University of Calcutta, India. She has been pursuing her Ph.D. degree at the same University in the area of biomedical image and signal processing. She has been employed in a project at the Computer Vision and Pattern Recognition unit of the Indian Statistical Institute, Kolkata, India.

Dr. M. Mitra was born in India in 1961. The author received her B.Tech, M.Tech & PhD (Tech) degrees in 1987, 1989 and 1998, respectively, from the University of Calcutta, Calcutta, India. At present she is Reader in the Department of Applied Physics, University of Calcutta, India, where she has been actively engaged in both teaching and research in Instrumentation. She is the co-author of 32 research papers pertaining to the problems of biomedical signal processing, data acquisition and processing modules and fault analysis.

B.B. Chaudhuri, received his B.Sc (Hons), B.Tech and M.Tech degrees from Calcutta University, India in 1969, 1972 and 1974, respectively, and his Ph.D. degree from the Indian Institute of Technology, Kanpur in 1980. Currently, he is the Head of the Computer Vision and Pattern Recognition Unit of Indian Statistical Institute. His research interests include pattern recognition, image processing, computer vision, natural language processing and digital document processing. He has published about 200 research papers in reputed international journals, conference proceedings and edited books. He was awarded the Sir J.C. Bose Memorial Award for his best engineering science-oriented paper in 1986, the M.N. Saha Memorial Award (twice) for best application-oriented papers in 1989 and 1991, the Homi Bhabha Fellowship award in 1992 for OCR of the Indian Languages and computer communication for the blind, Dr. Vikram Sarabhai Research Award in 1995 for his outstanding achievements in the fields of Electronics, Informatics and Telematics and the C. Achuta Menon Prize in 1996 for computer-based Indian language processing. He is a member secretary (Indian Section)

of the International Academy of Sciences, Fellow of International Association of Pattern Recognition, Fellow of National Academy of Sciences (India), Fellow of Institution of Electronics and Telecommunication Engineering and Fellow of the Indian National Academy of Engineering. He is serving as associate editor of Pattern Recognition (Elsevier), Pattern Recognition Letters (Elsevier) and VIVEK. In 1999, he was elected as a Fellow of Internal Association of Pattern Recognition. In the year 2000 he was honoured with the fellowship of IEEE (Institute of Electrical and Electronics Engineers).