System for Acquisition and Analysis of Transesophageal ECG

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Abstract – **In this paper, a system for acquisition and processing of transesophageal electrocardiogram (TEECG) is described. The system is intended to support the expert analysis in terms of diagnosis of abnormal electrical activity in the heart. The proposed low power acquisition subsystem assures excellent signal-to-noise ratio (SNR) and wideband coverage. The expert analysis is supported by automatic segmentation of the signal as well as Self-Organized Map (SOM) based clustering procedure.**

Keywords – **Esophageal electrocardiography, ECG, clustering, SOM.**

I. Introduction

The acute conduction abnormalities in the heart rhythm are some of the most common causes for hospitalization in the coronary care units. In some cases the differential diagnosis is troubled because of poor visualization of the P wave seen using the conventional 12-lead electrocardiography (ECG).

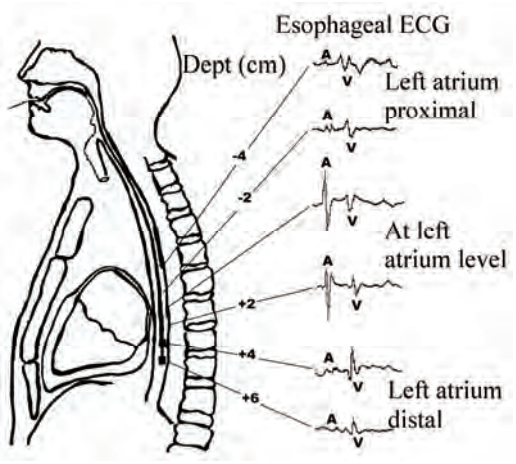

Fig. 1. Transesophageal electrocardiography and P wave morphology depending on probe position [1]

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The TEECG [1] is a diagnostic tool in which the electrodes are formed as an esophageal probe (Fig. 1). This probe is passed into the human esophagus usually under anesthesia. The anatomic closeness of the probe to the human heart as well as the lower electrical impedance give the possibility to achieve signal relatively free of noise and artifacts, thus the visualization of some weak ECG components is considerably improved (Fig. 2).

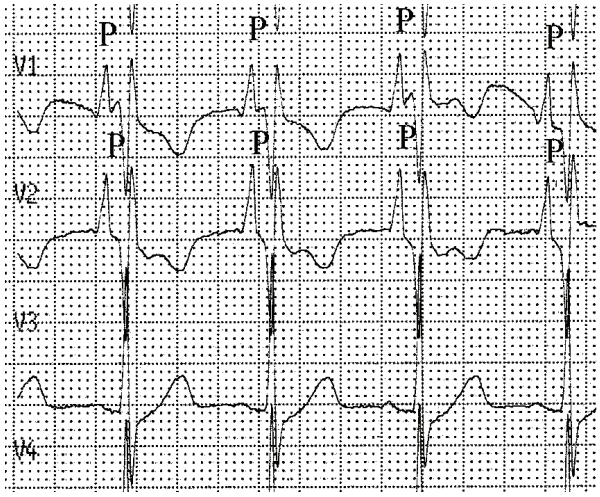

Fig. 2. Transesophageal ECG recordings (V1 and V2) compared with conventional surface ECG (V3) [1]

The method was used for first time in 1906 when an esophageal probe was inserted into the esophagus of a professional sword swallower [2]. Since 70's this technique has been used mainly to analyze atrial arrhythmias [3]. In recent years the interest concerning this method has been renewed [4].

The main challenge in such signal acquisition is the noise level, because the frequency band has to be much wider than conventional ECG registration devices. The frequency band has to cover the range from DC level up to 0.5-1kHz.

This paper introduces a system for acquisition and analysis of TEECG signals. The remainder of the paper is organized as follows: in section II is described the subsystem for signal acquisition; section III continues the work with TEECG signal processing and analysis; in section IV some experimental results and brief discussion are given; section V concludes the work and some aspects for future investigation are mentioned.

II. TEECG Signal Acquisition

The signal acquisition subsystem is based on integrated analog front-end for biopotential measurements type ADS1298 made by Texas Instruments [5]. The concept is to

use Analog-to-Digital Converters (ADC) with very high resolution (24 bit) and amplifiers with relatively low gain (1-12), thus the analog processing of the signals is minimized. A simplified block diagram of the described subsystem is shown in Fig. 3.

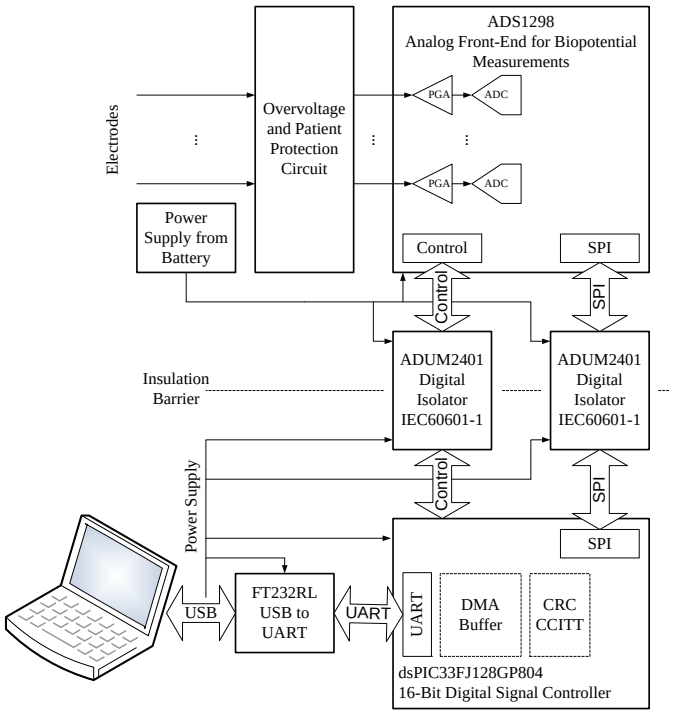

Fig. 3. Simplified block diagram of the subsystem for TEECG signals acquisition

The electrical safety of the patient is assured using digital isolators, which meet the standard IEC60601-1 [6]. The insulation barrier is placed between the analog front-end and the signal controller in order to minimize the battery consumption as well as to decouple the low noise signal acquisition part from digital transients. A Direct Memory Access (DMA) buffer is formed into the RAM memory of the signal controller for fast data transfer between Serial Peripheral Interface (SPI) and Universal Synchronous Receiver Transmitter (UART). The UART baud rate is 921 600 bps. The data is transmitted to the personal computer via UART to USB converter using 999 bytes long packets. The integrity of each packet is assured with 16-bit Cyclic Redundancy Check (CRC) with polynomial according to CRC-CCITT. The sampling rate can be either 1kHz or 2kHz.

III. TEECG Signal Analysis

The signal analysis subsystem is intended only to support expert decision. A simplified block diagram of the proposed sequence is shown in Fig. 4. As can be seen the referent surface ECG taken from external leads is used to determine the positions of R-peaks and the approximate positions of the middles of the baseline between T and next P wave. The R-peaks are found using the algorithm described in [7]. These positions are used to segment the TEECG into subsets which consist of PQRST complexes.

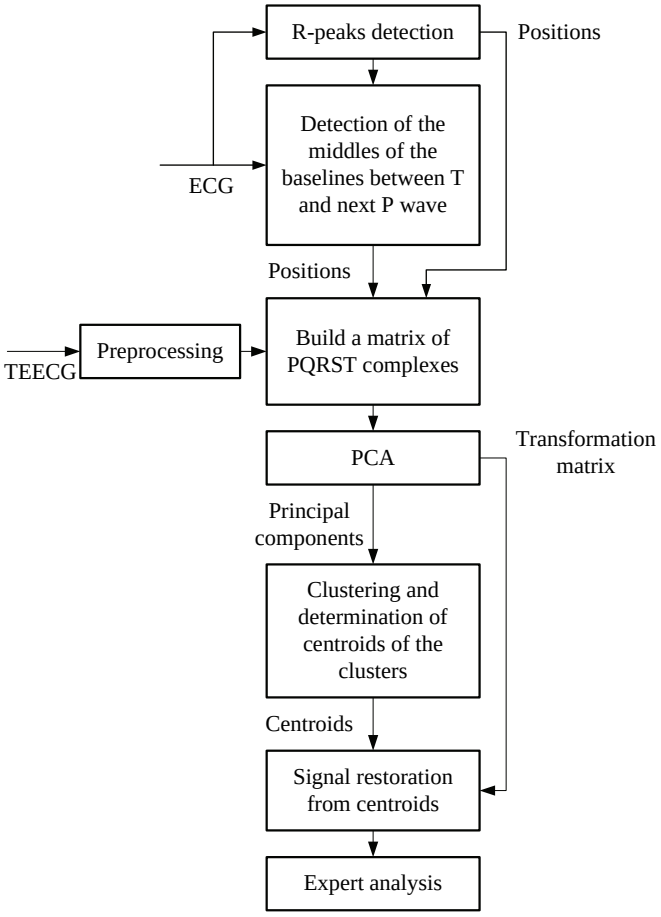

Fig. 4. Sequence for TEECG signals analysis

The rows of the input matrix $\mathbf{X} = \left[x_{ij} \right]_{N \times M}$ are arranged form the PQRST complexes in such way R-peaks are found in the middle column. The next procedure is to perform Principal Component Analysis (PCA) on the matrix $\mathbf{X}$ in order to reduce the very high dimensionality of the input data. PCA is a well known statistical technique for dimensionality reduction based on eigendecomposition, [8]. Let the input data be normalized in terms of unit standard deviation and zero mean according to:

$$\mathbf{Z} = \left[z_{ij} \right]_{N \times M} = \frac{1}{\mathbf{u}\boldsymbol{\sigma}} . \left(\mathbf{X} - \mathbf{u}\boldsymbol{\mu} \right), \tag{1}$$

where $\boldsymbol{\sigma} = \left[\sigma_1, \sigma_2, ..., \sigma_M \right]$ is the vector of standard deviation of $\mathbf{X}$, $\boldsymbol{\mu} = \left[\mu_1, \mu_2, ..., \mu_M \right]$ is the mean vector of $\mathbf{X}$, $\mathbf{u}$ is a column vector of units with number of elements N .and the operator "." denotes Hadamard product. The key procedure is to solve the eigendecomposition of the covariance matrix of the normalized input matrix $\boldsymbol{\Sigma}_Z = \left[\sigma_{Z,ij} \right]_{M \times M} = \frac{1}{N-1} \mathbf{Z}\mathbf{Z}^T$:

$$\mathbf{\Sigma}_Z \mathbf{V} = \mathbf{V}\mathbf{\Lambda}\,, \tag{2}$$

where $\mathbf{V} = \left[v_{ij} \right]_{M \times M}$ is a matrix which columns are the eigenvectors of $\mathbf{\Sigma}_Z$ and $\mathbf{\Lambda} = \left[\lambda_{ij} \right]_{M \times M}$ is a diagonal matrix of corresponding eigenvalues. The vectors in $\mathbf{V}$ and eigenvalues in $\mathbf{\Lambda}$ are rearranged in descending order of the eigenvalues. This leads to resulting matrices $\mathbf{V}' = \left[v'_{ij} \right]_{M \times M}$ and $\mathbf{\Lambda}' = \left[\lambda'_{ij} \right]_{M \times M}$ respectively. The matrix of principal components $\mathbf{Y} = \left[y_{ij} \right]_{N \times M}$ is:

$$\mathbf{Y} = \mathbf{V}'\mathbf{Z}\,. \tag{3}$$

As a result the covariance matrix of the principal components $\Sigma_Y = \left[\sigma_{Y,ij} \right]_{M \times M} = \frac{1}{N-1}\mathbf{Y}\mathbf{Y}^T$ is diagonalized. The elements of the vector of Mean Squared Error (MSE) between the original data $\mathbf{X}$ and restored data $\hat{\mathbf{X}}$ when using a reduced number of principal components $\mathbf{mse}\left(\hat{\mathbf{X}}\right) = \left[mse\left(\hat{\mathbf{X}}\right)_1, mse\left(\hat{\mathbf{X}}\right)_2, ..., mse\left(\hat{\mathbf{X}}\right)_M \right]$ are [9]:

$$mse\left(\hat{\mathbf{X}}\right)_i = \sum_{j=1}^{M} \lambda'_{jj} - \sum_{k=1}^{i} \lambda'_{kk}, i = 1, ..., M\,. \tag{4}$$

The new data dimensionality $L \le M$ is found according to:

$$L = \min_i \left(i = 1, ..., M \right) \left| mse\left(\hat{\mathbf{X}}\right)_i \le mse_{thr}\,, \right. \tag{5}$$

where mse_{thr} is a given threshold value. The matrix of principal components with reduced dimensionality is $\hat{\mathbf{Y}} = \left[\hat{y}_{ij} \right]_{N \times L}$ and its elements are : $\hat{y}_{ij} = y_{ij}, i = 1, ..., N; j = 1, ..., L$.

The clustering procedure is performed on $\hat{\mathbf{Y}}$ and centroids are formed from the resulting clusters as a mean vector or the codebook vectors of SOM can be used. The restored PQRST complex $\hat{\mathbf{x}}_c$ from each centroid $\hat{\mathbf{y}}_c$ is calculated according to [10]:

$$\hat{\mathbf{x}}_c = \mathbf{\sigma}.\left(\mathbf{W}\hat{\mathbf{y}}_c^T \right)^T + \mathbf{\mu}\,, \tag{6}$$

where $\mathbf{W} = \left[w_{ij} \right]_{M \times L}$ is the transformation matrix whose elements are: $w_{ij} = v'_{ij}, i = 1, ..., M; j = 1, ..., L$.

The clustering procedure is based on a variant of SOM called Growing Hierarchically Self-Organized Maps (GHSOM) in which the SOM topology doesn't have to be set a priory [11]. As usual the Euclidean distance serves as similarity measure.

IV. Experimental Results

The hardware part of the system was tested with the built-in square wave test generator with amplitude of 1mV. Next the noise level was investigated by shorting the input terminals. The achieved value is $5.1\mu V_{RMS}$ at 1kHz sampling rate and gain set to 6.

Because the hardware subsystem hasn't passed clinical tests yet, a synthetic signal was used to validate the algorithm for analysis. It is suitable to use the signal proposed in [12]. The signal morphology was changed in order to resemble the typical TEECG waveform. Because the positions and morphology of P waves are in a special interest, a synthetic TEECG signals were prepared with 5 different amplitudes and 5 different positions of P waves. The total number of used signals is 10. The length of each signal is about 1min. An additive uniform noise was also added in the signal. The total number of the PQRST complexes is 640 (Fig. 5)

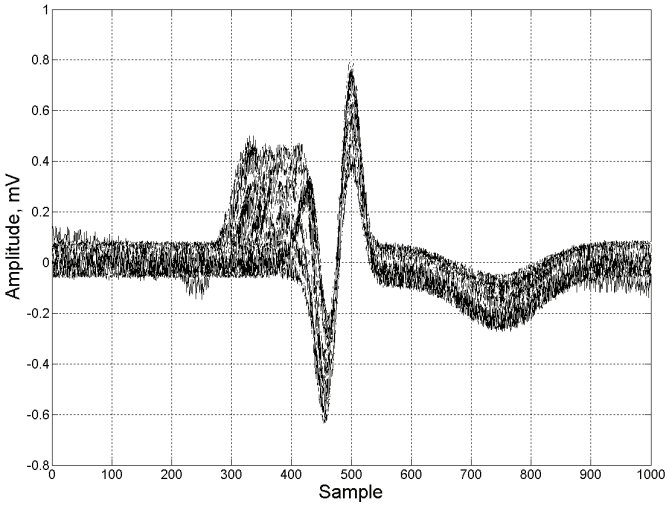

Fig. 5. Common plot of all synthetic PQRST complexes for clustering

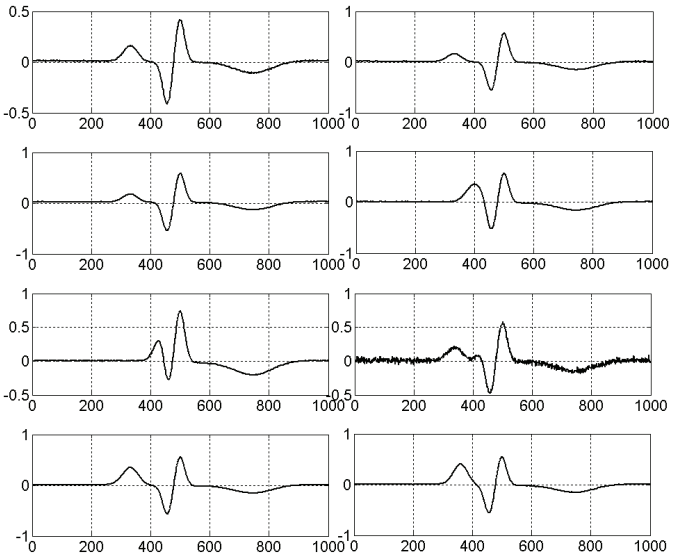

Fig. 6. Restored PQRST complexes from the centroids of the clusters

The restored signals from the centroids after GHSOM clustering are shown in Fig. 6. The clustering was performed on data with dimensionality reduced from 1000 down to 200. As can be seen the back restoration from reduced number of principal components also performs denoising.

V. Conclusion

In this paper, a system for transesophageal electrocardiogram acquisition and analysis was presented. The achieved SNR from acquisition subsystem is high considering the wide frequency range. The analysis algorithm performs correct also. In future it is planned to investigate the usefulness of PCA applied on multichannel transesophageal ECG. The obtained principal components can reveal information, which could be associated with particular cardiac disorder.

References

[1] Б. Бойчев, *Основи на трансезофагеалната електрокардиостимулация*, Казанлък, Янита ЯС, 2010.

[2] M. Cremer, "Über die direkte Ableitung der Aktionsströme des menschlichen Herzens vom Ösophagus und über das EKG des Föten", Münch Med Wschr, vol. 53, pp. 87-93, 1906.

[3] J.M. Jenkins, D. Wu, R.C Arzbaecher, "Computer diagnosis of supraventricular and ventricular arrhythmias. A new esophageal technique", Circulation, vol. 60, no. 5, pp. 977-987, 1979.

[4] B. Boychev, S. Rahimi, M. Mihalev, V. Kushev, "Transesophageal electrocardiography - methods and importance", Bulgarian Cardiology, vol. 4, pp. 31-50, 2002.

[5] Texas Instruments, "Low-Power, 8-Channel, 24-Bit Analog Front-End for Biopotential Measurements", http://focus.ti.com/lit/ds/symlink/ads1298.pdf.

[6] *International Standard IEC 60601-1*, Third edition, 2005, http://www.jbhealthcare.com/download/info_iec60601-1%7Bed3.0%7Den_d.pdf

[7] Y. Velchev, "ECG QRS Identification Using Morphological Filtering and Histogram Analysis", Computer & Communications Engineering, ISSN 1314-2291, vol.4, no.1, pp. 51-55, 2010.

[8] F. Castells, P. Laguna, L. Sornmo, A. Bollmann, J. Millet-Roig, "Principal component analysis in ECG signal processing", EURASIP Journal on Applied Signal Processing, vol. 2007, no. 1, pp. 98-119, 2007.

[9] S. Sanei, J. A. Chambers, *EEG Signal Processing*, Wiley-Interscience, 2007.

[10] V. Franc, V. Hlavac, "The statistical pattern recognition toolbox", 2004, http://cmp.felk.cvut.cz/cmp/software/stprtool/index html.

[11] M. Dittenbach, D. Merkl, A. Rauber, "The Growing Hierarchical Self-Organized Map", Proceedings of the Int'l Joint Conference on Neural Networks (IJCNN' 2000), pp. VI-15-VI-19, 2000.

[12] P. McSharry, G. Clifford, L. Tarassenko, L. Smith, "A dynamical model for generating synthetic electrocardiogram signals," IEEE Transactions on Biomedical Engineering, vol. 50, no. 3, pp. 289-294, 2003.