Methods of Visualization and Analysis of Cardiac Depolarization in the Three Dimensional Space

Sergei Artemov[1], Bernd Krause[2]
[1]Perm National Research Polytechnic University - Electrotechnical Department
Prof. Pozdeev str. 7, 614013, Perm, Russia
[2]Anhalt University of Applied Sciences - Computer Science and Languages Department
Lohmannstr. 23, 06366, Koethen, Germany
E-mail: [1]art-sa@bk.ru, [2]bernd.krause@inf.hs-anhalt.de

***Abstract*—Research analysis of electrocardiograms (ECG) today is carried out mostly using time depending signals of different leads shown in the graphs. Definition of ECG parameters is performed by qualified personnel, and requiring particular skills. To support decoding the cardiac depolarization phase of ECG there are methods to analyze space-time convolution charts in three dimensions where the heartbeat is described by the trajectory of its electrical vector. Based on this, it can be assumed that all available options of the classical ECG analysis of this time segment can be obtained using this technique. Investigated ECG visualization techniques in three dimensions combined with quantitative methods giving additional features of cardiac depolarization and allow a better exploitation of the information content of the given ECG signals.**

***Keywords:* ECG, PCA, cardiac depolarization.**

I. Introduction

The representation of heart activity is formed as a time sequence of potential difference with respect to different points on the human body. There a two types of ECG: session and continuous – use as source data here, it need for keeping track abnormality in heart behavior.

If we imagine the body as a three-dimensional object it is possible to measure the summary vector of potentials changes in space and time. Here we refer to a measurement of this electrical heart vector in a orthogonal X,Y,Z-coordinate system with a given sampling rate in time (e.g. 1 kHz). Based on these three dimensional signals and a background knowledge of heart muscle structure - including knowledge about pulses excitation, formation and propagation - it is possible to analyze the heart beats and eventually identify pathologies. It is a challenging task to visualize ECG and analyze them in three dimensional space in a way that would be most understandable to medical staff and to get as much data as possible for further analysis and data mining tasks.

From three dimensional signals clearly visible additional ECG features are derived, for example, the rotation of the electrical heart angle, the dynamic characteristics of angle changes and unforeseen changes n heart position relative to the body which may be a result of respiratory movements and so on.

II. Classical ECG Representation

The standard approach to visualize ECG signals is time charts of single leads. Parameters such as the rhythm frequency, the amplitude of the peaks, the beats regularity, the average heart electrical angle, as well as various kinds of deviations, and other can be evaluated. Mostly evaluation is carried out through a review of the peaks and the parts of the signal.

The most interesting part is the QRS complex because here cardiac depolarization of the heart muscle occurs. This is the most dynamic activity of the heart. Figure 1 shows graphs [1] of two beats with similar characteristics as beat amplitudes and morphology, where morphology is characterize by the peaks Q, R, S.

First beat is used as reference, but second one comes from a beat which is followed directly by tachycardia.

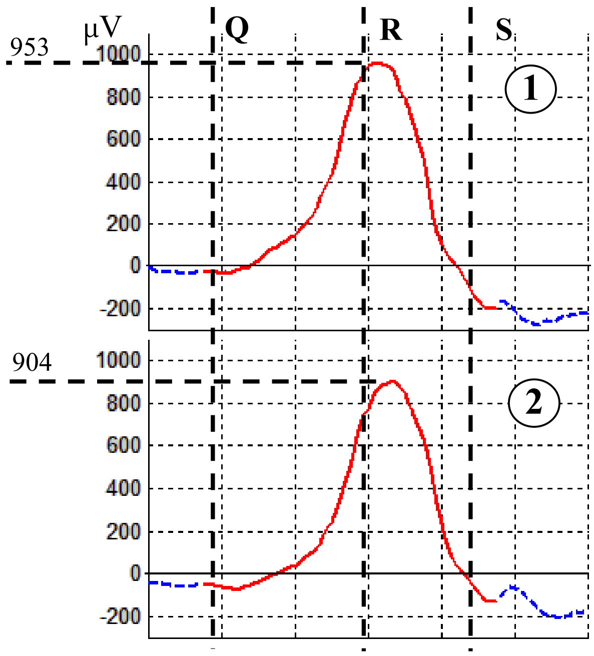


Fig. 1. Comparison of the QRS graphs of beats.

At a first view the difference between the graphs are invisible, they have a similar shape, amplitude, pulse length. But it is difficult to distinguish morphological differences in their shape. We have a similar situation with other leads. To reveal differences in behavior we need joint information of all three leads.

III. Three Dimensional Representation

To improve the ability to detect differences in behavior of the heart a three dimensional consideration of ECG is necessary.

The initial data are the three leads of X,Y and Z components of a heart vector in three-dimensional space which describe time-space trajectory of this vector. The new approach allows estimate the interdependency of the leads and determine the invisible changes in the time diagram [2][3]. Figure 2 shows a graph of a QRS loop of a beat in the three-dimensional space with marked QRS peaks.

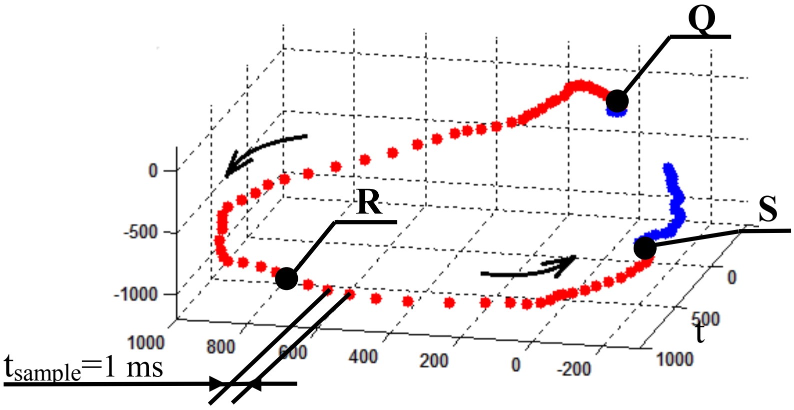


Fig. 2. A three-dimensional representation of QRS part of a beat.

The graph in figure 2 represents a loop where the heart vector runs through its trajectory with a specific kind of bending, twisting, compression and expansion - the dynamic characteristics of the signal.

Figure 3 shows images of the previous beats (from Fig. 1) in three dimensions. The loops are presented from different perspectives. The beats have similar morphologies which are rotated in space.

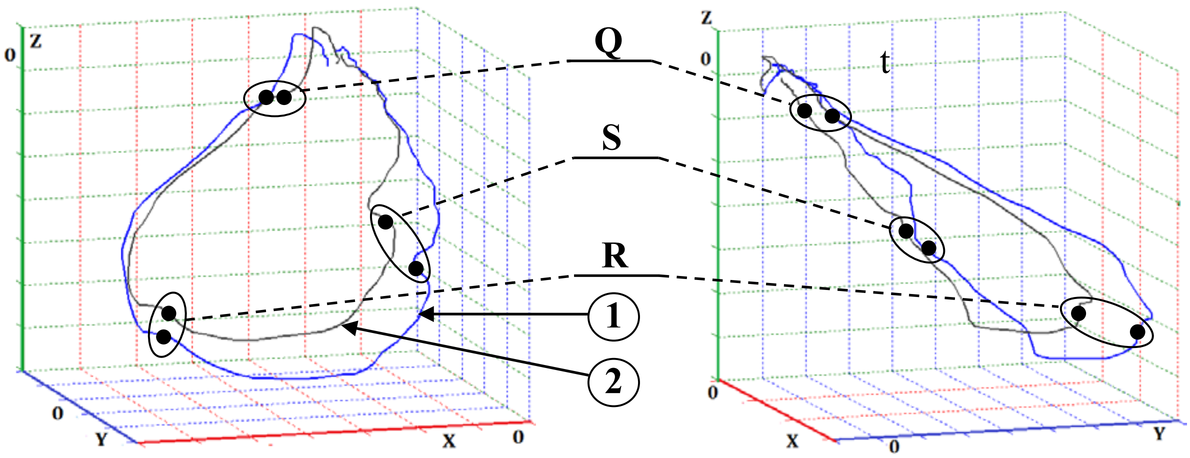


Fig. 3. Beats graphics with different views.

IV. Approximation of the Whole QRS Complex by Plane

Three dimensional visualization of ECG is not sufficient for further quantitative data analysis. For detailed data analysis and data mining tasks additional features are necessary witch give additional information.

The simplest way to represent QRS loop is the mean vector of heart electric potentials.

The classical generalization of this dimensions reduction technique is the principal component analysis (PCA). This technique allows the transformation of a set of points into a space with a smaller dimension k>0. For our purpose a two dimensional plane is adequate.

Figure 4 shows the rotated approximating planes of the two beats from figure 3. Obviously the trajectories of both beats are more similar in their individual planes than in other representations. That’s why, it is important to identify these planes and their mutual relation, including the rotation which is necessary to match both trajectories as good as possible.

PCA method description [4][5]:

Given a finite set of vectors (points):

$$x_1, x_2, \ldots, x_m \in \mathbb{R}^n \tag{1}$$

where in our case we have $n = 3$ and $x_i = (X(t_i), Y(t_i), Z(t_i))$ with equidistant $t_1 < t_2 < \cdots < t_m$. Generally the task is to find (for $k = 0,1, \ldots, n-1$) linear subspaces L_k,

$$L_k \in \mathbb{R}^n \qquad (2)$$

such that the sum of the squared distances from the x_i to L_k was minimal

$$\sum_{i=1}^{m} dist^2(x_i, L_k) \rightarrow min \qquad (3)$$

where $dist(x_i, L_k)$ is the Euclidean distance from the point to the linear manifold. To solve this problem one has to subtract the mean of the vectors $x_1, x_2, \ldots, x_m$ from each point to center the data around the origin.

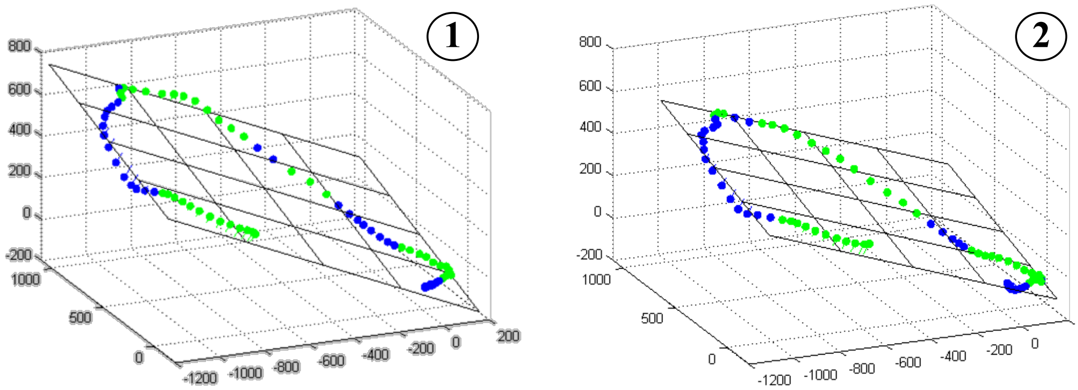


Fig. 4. Approximating planes for two beats.

Then the Hesse normal form of the plane (k=2) with normal vector n allows to express the sum of these distances by

$$\sum_{i=1}^{m} (n^T x_i)^2 = n^T \left(\sum_{i=1}^{m} x_i x_i^T\right) n \rightarrow min \qquad (4)$$

where the centered data are also denoted by $x_1, x_2, \ldots, x_m$. Since the Matrix $A = \sum_{i=1}^{m} x_i x_i^T$ is symmetric and positive definite it has three strictly positive eigenvalues and an orthogonal system of three (normalized) eigenvectors. These vectors are the principal component vectors.

The approximating plane is spanned by the first two eigenvectors of A and its normal vector n is orthogonal to them, that is, it is the eigenvector to the minimal eigenvalue which minimizes (4).

Figure 5 shows again the approximating planes of the previous two beats (Figure 3, 4) in a common coordinate system. The graph displays the normal vectors of both planes, called global orientation, and the exact rotation expressed by the angle α between these normal vectors.

On the basis of medical arguments – this rotation can be explained by breathing, movement or specific orientation of heart for each person.

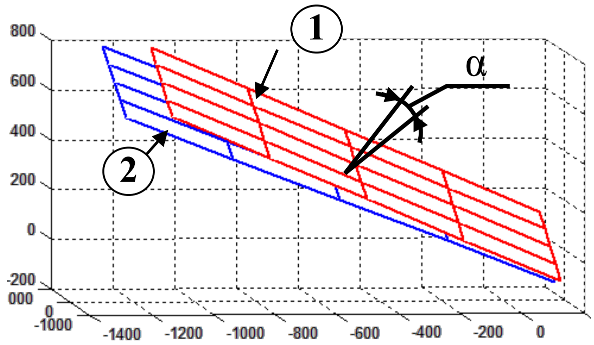
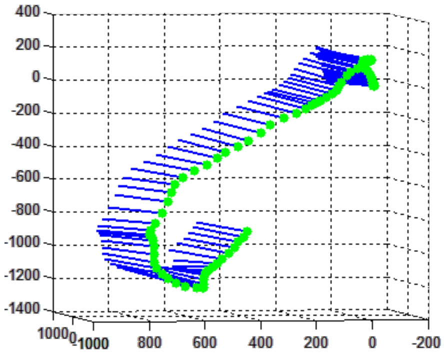


Fig. 5. Approximating planes of two beats.

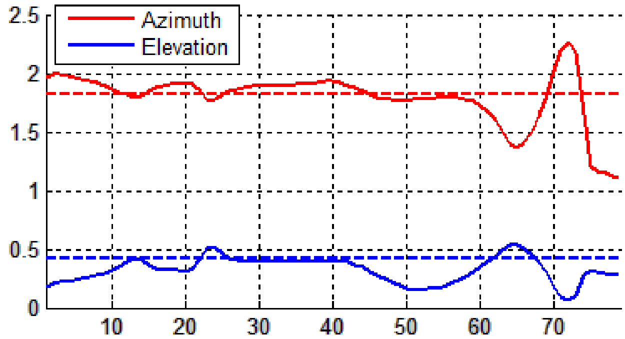
V. Local Approximation of QRS Segments

The previous example describes how to find approximating plane and global orientation n of QRS complex based on all point of the loop. For finding a corresponding local orientation n_i the approximating plane is calculated only for the part of the loop given by a sliding time window Δt. Thus by shifting time window for each point t_i (the midpoint of the window) we get the local orientation vectors n_i.

In figure 6-a local orientation vectors are shown for Δt=25ms. In figure 6-b the local orientation vectors are displayed. Additionally, the dashed lines indicate the global orientation vector.



a - three dimensional representation



b – two dimensional representation

Fig. 6. Graphs of local orientation vectors.

VI. Conclusion

Representation of ECG depolarization part in three-dimensional form is one of the new ways of presenting information. For further clear data representation such visualization methods are useful. They give directions for further investigations and analysis. Based on this additional data are available that show features and relations between the individual output leads as new signals.

These data allow consider additional data for learning and data mining tasks and increase accuracy of methods and diagnostic abnormalities in heart behavior.

Furthermore, this approach can be applied to other parts of ECG which also allow predicting the behavior of heart beating such as late potentials parts ST complex etc.

References

[1] M.-E. Nygards, L. Sornmo,"Delineation of the QRS complex using the envelope of the ECG" - Medicine and biology, 1983, No 21 pp.538-547.

[2] M. Kotas, "Projective Filtering of Time-Aligned ECG Beats" – IEEE transactions on biomedical engineering vol.51, No.7, 2004, pp. 1129 – 1139.

[3] L.G. Tereshchenko, L. Han, A. Cheng, "Beat-to-beat three-dimensional ECG variability predicts ventricular arrhythmia in ICD recipients" – Heart Rhythm Society, 2010, pp. 1606 – 1613.

[4] W Müller, T. Nocke, H. Schumann , "Enhancing the visualization process with principal component analysis to support the exploration of trends" - Asia-Pacific Symposium on Information Visualization, 2006.

[5] I.T. Jolliffe, "Principal Component Analysis", Springer, New York, 2002.