AUTOMATIC ECG ANALYSIS FOR PRELIMINARY AND DETAILED DIAGNOSTICS BASED ON SCALE-SPACE REPRESENTATION

Natalie Belous, Gleb Kobzar

Abstract: A novel approach of automatic ECG analysis based on scale-scale signal representation is proposed. The approach uses curvature scale-space representation to locate main ECG waveform limits and peaks and may be used to correct results of other ECG analysis techniques or independently. Moreover dynamic matching of ECG CSS representations provides robust preliminary recognition of ECG abnormalities which has been proven by experimental results.

Keywords: electrocardiogram, ECG analysis, express-diagnostics, curvature scale-space, dynamic programming, dynamic time wrapping.

ACM Classification Keywords: I.5 Pattern Recognition.

Introduction

Automatic diagnostics of cardiac diseases is the traditional task of medical cybernetics. At current large experience is accumulated in this area. In particular attempts of complete automation of heart activity diagnostics have failed to be enough robust comparatively to traditional human diagnostics. The most essential stage of traditional ECG analysis is recognition of its major elements, which consist of finding out the QRS-complex, selection of it's characteristic points (tops of Q, R, S indents, scopes of indents and their borders).

The results of element analysis (annotation) and measuring of their parameters are used for ECG interpretation with purpose of correct diagnosis. Two basic categories of algorithms, applied in different systems of automatic diagnostics currently exist. Algorithms that design logic of doctor-diagnostician fall into the first category. The algorithms of the second category as a rule are based on the methods of multidimensional statistical analysis and theory of possibility.

Indisputable advantage of medical algorithms - in possibility rapid decision realization. It is conditioned by the fact that they concentrate experience of diagnostics accumulated in medicine and do not require preliminary teaching. Diagnostic possibilities of such algorithms are limited to the modern level of medicine development and quality of concrete algorithms – to the competence of persons assembling them as technicians and medics. Nevertheless location of necessary for traditional diagnostics points on ECG is not a trivial task.

Advantage of nonmedical diagnostic algorithms is that they can utilize any parameters of electrocardiogram representation. Due to it backlogs of information which in clinical practice remain unutilized appear accessible for such algorithms. The lack of these algorithms is complication of teaching and readiness. In case substantial difficulties are related to the selection of the well probed patients with diseases which an automat must learn to distinguish. Nevertheless, the algorithms of the second category are considered more perspective, because access to the new information should make diagnostics more effective.

Various automatic algorithms of the second group have been proposed, such as the threshold-crossing intervals X and the auto-correlation function [1] and algorithms based on neural-networks [2]. Time—frequency (t — f) analysis [3] and wavelet analysis [4] have also been used. All these algorithms suppose finding one special disease or detecting that ECG signal could be classified as normal.

This article focuses on building technique of ECG analysis that is able to support traditional diagnostics providing waveform limits and peaks and preliminary diagnostics to be performed at home or in non-medical environments by professional doctors or even users having no medical knowledge. The preliminary diagnostic results correspond to three possible binary decisions: normal ECG, disease, not known.

We propose a novel approach of normal ECG recognition which is based on scale-scale signal representation used for geometric object shape recognition previously - curvature scale-space (CSS) and our dynamic programming algorithm for matching ECG signal represented as CSS descriptors. Though the idea of scale-scale signal representation for ECG analysis is far not new [5] including the fact that wavelets are multi-scale by nature the approach proposed may have some valuable advantages over existing scale-scale approaches.

The article is organized in 4 main sections. The first section describes CSS briefly as it's not a well-known technology in medical signal processing. The second section introduces how to apply CSS to ECG signals. The third section describe waveform limits and peaks location technique. The forth section focuses on dynamic programming matching algorithm proposed. And the last chapter describes some tests performed.

Curvature Scale Space representation of shapes

The Theory of Scale-Space Signal Representation was introduced by Vitkin and Coendric in 1983. The methodology consist in embedding a measured signal into a one-parametric family of derived signals, the scale-space, where the parameter, denotes scale parameter $\sigma \in \Re_+$, is intended to the current level of scale. For a signal $f : \Re \to \Re$, the scale-space representation $L : \Re \times \Re_+ \to \Re$ is defined as [6]:

$$L(x;0) = f(x). \tag{1}$$

And representation at coarser scales are given by convolution of the given signal with Gaussian kernels of successively increasing width:

$$L(x;\sigma) = g(x,\sigma) * f(x). \tag{2}$$

Curvature Scale-Space was introduced later by Mokharitan for geometric object shape representation as follows [7]. Having curvature of each closed contour $L(x;\sigma)$ points calculated, curvature zero-crossing points can be found easily. Then Curvature Scale-Space is built by locating zero-crossings in $(x;\sigma)$ space (u - normalized arc length, σ - Gaussian filter kernel size [7]. The resulting CSS can be represented as a binary image of CSS. Cross-sections of CSS by horizontal lines define position of zero-crossing points on the corresponding $L(x;\sigma)$.

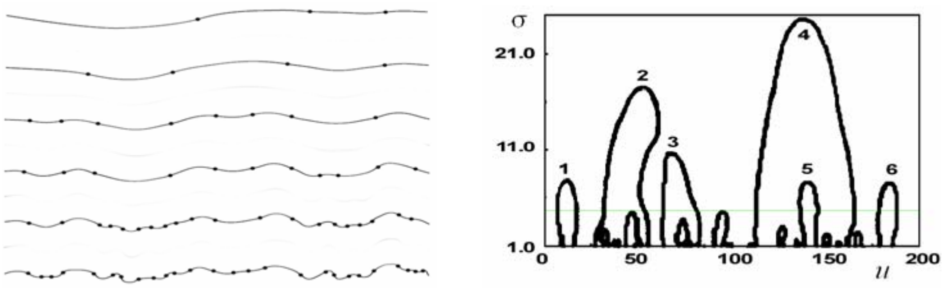
It is obvious that CSS images of normalized curves are invariant to affine transformations and noise. Rotation of an object causes circular shift of it's CSS representation (fig.1a,b). The same effect is caused by the change of contour starting point. Because of normalization scaling also don't affect the view of CSS. In addition noise do not effects high scales of CSS (the threshold may be determined easily).

These properties of CSS image are used for effective representation and recognition of object shapes. It should be also noted that successful identification of shapes based on CSS representation don't require CSS Images themselves but arc maximums only []. The set of CSS maximas consists of pairs and form well-known CSS description which was selected as one of the main shape descriptors for MPEG-7 standard.

Application of CSS to ECG Representation

Curvature Scale-Space representation and matching process was introduced for closed curve contours only and are not suitable for signal analysis. We will show that it is possible to adapt CSS for ECG representation in this section and ECG matching based on such representation in the next section.

As curvature scale-space methodology has it's root's in multi-scale signal representation area switching back from closed contours to signal segments representation is very easy. Signal curvature zero-crossing points may be acquired in the same way calculating the first and the second discrete differences (fig. 1a).



a b

Fig. 1. Evolution of the signal and appropriate curvature zero-crossing points:
a – zero-crossings at different scales, b – CSS image and valuable arcs.

CSS images of such zero-crossings found on each scale of ECG signal evolving will look the same as for geometric object shape contour (fig.1b). The only difference here is in representation of CSS image maxima which affects matching process also. As closed contour may be started to detect from different points CSS image is also circular. In a difference an ECG signal starts and finishes at certain points. So CSS image for ECG and the set of maxima as well is not be shifted during acquisition and matching process.

ECG Waveform limits and peaks location

The most valuable result achieved using CSS for ECG representation is ability of physiologically correct and stable location of main waveform limits and peaks. The algorithm of waveform location based on wavelet QRS detection is described below.

Wavelet QRS detection algorithm is used first to locate largest peaks of ECG QRS complexes as it has been proven to provide the most precise and stable to noise QRS detection [9]. Unfortunately this algorithm is not able to provide correct waveform limit points automatically and require frequency parameter setup depending on the shape of waveforms (Fig.2).

Physiologically correct position of waveform limits are at points of maximum slope of the first order ECG derivative [10].

The CSS representation of ECG signal is built as described previously. First order ECG derivative is used instead of actual ECG signal to provide physiologically correct location of waveform limits at points of maximum slope which in the case of CSS are zero-crossings of the first order ECG derivative.

Having the largest QRS peak located using wavelet detector the cross-section scale level is then determided to locate the rest of waveform limits and peaks by the highest scale intersection point of QRS largest peak position and CSS arcs (green line at Fig.2).

The rest of points are located as follows. Correct QRS left and right limits lie at the previous and the next crossing points of the cross-section line accordingly.

Correct P wave maxima (positive or negative or maxima of bi-phases P-wave) and the left limit is located as two crossing points before the QRS left limit. Correct T wave maxima and two limits are located as three crossing after the point next to the QRS right limit.

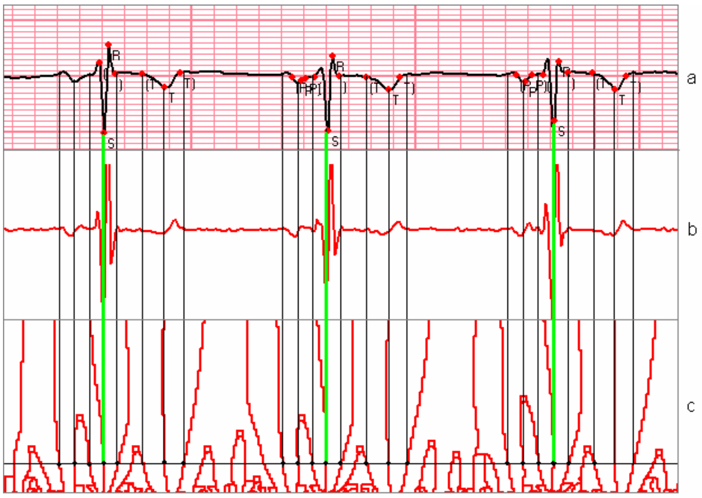


Fig. 2. ECG waveform limits and peaks location:
a – ECG annotated using wavelet approach,
b – ECG derivative,
c – CSS of ECG derivative with a cross-section applied

Figure 2 shows that QRS limits located by the proposed algorithm are physiologically more correct than ones given by wavelet algorithm and allow correct and easy S and Q wave location. T and P wave limits are also shown to be more precisely located.

It is also seen that noise does not effect much correct waveform location by the algorithm which is caused by the nature of CSS representation. All noise affected CSS arcs are laying on the lowest scales of CSS (Fig.2c). Nevertheless large high-frequency noise may affect the results and addition high-pass filtration would be required then.

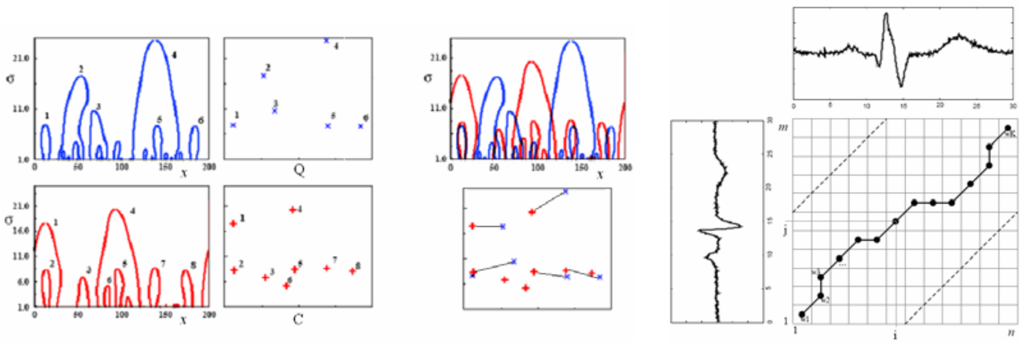
Matching CSS Representations of ECG for preliminary diagnostics

Matching algorithm for preliminary diagnostics is also proposed based on CSS representation of ECG. Every signal in the database is represented by the locations of the maxima of it's CSS images. Matching algorithm compares two sets of maxima and assigns a matching value to them which represent the similarity between the actual boundaries of objects (Fig.3a). Obviously as the nature of curves differs for contours and signals matching algorithm of CSS representations introduced by Mokhtarian with its main principle to shift maximums is not suitable for CSS representations of ECG signals [7]. Moreover the algorithm will fail to match curves with large dissimilarities of structure distances (heart rhythm change).

A different algorithm of matching CSS representations of ECG based on dynamic programming is proposed. It is organized in the same way as Dynamic Time Warping (DTW).

Having two sets of maxima $Q= q_1,q_2,\dots,q_i,\dots,q_n$ ($q_i = (\sigma_i, x_i)$, where σ is a scale parameter and x is position of the maxima) and $C=c_1,c_2,\dots,c_j,\dots,c_m$ ($c_i = (\sigma_i, x_i)$) of length n and m respectively matching of these sets using proposed DP matching algorithm requires to construct an n-by-m matrix (DP matrix) where the (i^{th}, j^{th}) element of the matrix contains the distance $d(q_i,c_j)$ between the two points q_i and c_j (in a metric defined below). Each matrix element (i,j) corresponds to the alignment between the points q_i and c_j. This is illustrated in Figure 3b. A warping path W, is a continuous (in the sense stated below) set of matrix elements that defines a mapping between Q and C. The k^{th} element of W is defined as $w_k = (i,j)_k$ so we have:

$$W = w_1, w_2, \dots, w_k, \dots, w_K \qquad \max(m,n) , K < m+n-1$$



a b

Fig. 3. Dynamic matching of two ECG signals: a – CSS maximas, b – dynamic matching

The warping path is typically subject to several constraints:

- Boundary conditions: $w_1 = (1,1)$ and $w_K = (m,n)$, simply stated, this requires the warping path to start and finish in diagonally opposite corner cells of the matrix.

- Continuity: Given $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a-a'<=1$ and $b-b'<=1$. This restricts the allowable steps in the warping path to adjacent cells (including diagonally adjacent cells).

- Monotonicity: Given $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a-a'>= 0$ and $b-b'>= 0$. This forces the points in W to be monotonically spaced in time.

There are exponentially many warping paths that satisfy the above conditions, however we are interested only in the path which minimizes the warping cost:

$$\Omega(Q,C) = \min_{(Q',C',f)} \left\{ \begin{array}{l} \sum_{i=1}^{|Q|} \sqrt{(x^{-1}(q_i) - x^{-1}(f(q_i)))^2 + (\sigma(q_i) - \sigma(f(q_i)))^2} \\ + \sum_{q\in Q/Q'} \sigma(q) + \sum_{q\in C/C'} \sigma(c) \end{array} \right\} \qquad (3)$$

where $Q', C', |Q'|=|C'|$ - are subsets of Q, C accordingly,

$(x^{-1}(q_i) = x(q_i) - x(q_{i-1}), x(q_0) = 0$ - is a distance to previous CSS maxima (time interval).

The path can be found very efficiently using dynamic programming to evaluate the following recurrence which defines the cumulative distance $\gamma(i,j)$ as the distance $d(i,j)$ found in the current cell and the minimum of the cumulative distances of the adjacent elements:

$$\gamma(i,j) = d(q_i c_j) + \min\{\gamma(i-1,j-1), \gamma(i-1,j), \gamma(i,j-1)\} \tag{4}$$

where $\gamma(i,j)$ - accumulated cost of w_k DP table cell,

$d(q_i c_j)$ - wrapping cost in w_k which is calculated as follows:

$$\begin{aligned} d_{match}(q_i c_j) &= \sqrt{x^{-1}(q_i) - x^{-1}(f(q_i)))^2 + (\sigma(q_i) - \sigma(f(q_i)))^2} \\ d_{skipi}(q_i c_j) &= \sigma(q_i), d_{skipj}(q_i c_j) = \sigma(q_i) \end{aligned} \tag{5}$$

where $d_{match}(q_i, c_j)$ - distance for matching two points or a diagonal movement,

$d_{skipi}(q_i, c_j)$ - distance for skipping the point q_i or a horizontal movement,

$d_{skipj}(q_i, c_j)$ - distance for skipping the point q_j or a vertical movement.

Such formulation of $d(q_i,c_j)$ has already been proven in practical application of geometric shape matching as a part of Mokhtarian's algorithm.

Finally the cost of matching could be found in $\gamma(n,m)$ using backtracking algorithm while building the optimal path W.

Experimental Results

We have also evaluated our algorithm in terms of important interval values P duration QRS duration and QT interval. The evaluation has been done in terms of the standard deviation of the differences between intervals estimated by our algorithm (10.2ms), intervals measured by wavelet technique (12.3ms) and intervals measured from the mean referee estimates of CSE database (9.6ms) which proves better performance of proposed algorithm. 120 beats was used provided for program testing and 30 expert annotated beats contained in CSE.

Also 51 ECG signals was selected for preliminary diagnostics testing from the international ECG database PhysyoNet (Physikalisch-Technische Bundesanstalt – PTB, the National Metrology Institute of Germany).

Table 1. Distribution of classes

Diagnostic class	*Number of ECG signals*
Myocardial infarction	5
Cardiomyopathy/Heart failure	8
Bundle branch block	5
Dysrhythmia	4
Myocardial hypertrophy	5
Valvular heart disease	5
Myocarditis	5
Miscellaneous	4
Healthy controls	10
Total	51

Techniques of CSS representation and dynamic matching were realized as a computer program which was tested on the assembled database of ECG signals.

Following the well known technique of automatic ECG interpretation quality estimation [9] we assume that all database signals are verified (normal forms and pathological forms). Then counting up the general number of the followings events: correct classification of normal ECG (TN), improper classification of normal ECG as pathological (FP), improper classification of pathological ECG as normal (FN), correct classification of pathological ECG (TP).

In total, quality of ECG interpretation is calculated as "probability that classification is correct" according to the following formula:

$$TA = \frac{TP + TN}{TP + FP + TN + FN} 100\% \tag{6}$$

Thus according to experiment results TP=41, TN=9, FP=1, FN=0 and resulting TA=98%. After introduction of the third diagnostic result – “not known” FN=0 may be achieved. In the case if a user received “not known” result he can repeat the measurements. And if the same result achieved again it would be recommended to consult with professional doctor-cardiologist.

Conclusion

A novel approach of automatic ECG analysis based on scale-scale signal representation is proposed. The approach uses curvature scale-space representation to locate main ECG waveform limits and peaks and may be used to correct results of other ECG analysis techniques or independently. Moreover dynamic matching of ECG CSS representations provides robust preliminary recognition of ECG abnormalities.

The main advantage over existing waveform location techniques is physiologically correct and noise stable detection of waveform limits.

The main advantage of the approach over the existing preliminary diagnostic techniques is faster extraction process and matching process as it is done in CSS space. Experimental results show that the approach is quite robust for preliminary normal ECG recognition. It is planned to conduct larger tests on different ECG databases and comparative tests to compare the quality of diagnostics and the rapidness with other interpretation techniques.

Bibliography

[1] R.H. Clayton, A. Murray, R.W.F. Campbell, Comparison of four techniques for recognition of ventricular fibrillation of the surface ECG, Med. Biol. Eng. Comp. 31 (1993), pp. 111—117.

[2] K. Minami, H. Nakajima, T. Toyoshima, Real-time discrimination of ventricular tachyarrhythmia with Fourier transform neural network, IEEE Trans. Biomed. Eng. 46 (2) (1999), pp. 179—185.

[3] V.X. Afonso, W.J. Tompkins, Detecting ventricular fibrillation, IEEE Eng. Med. Biol. 14 (1995) pp. 152—159.

[4] A.S. Al-Fahoum, I. Howitt, Combined wavelet transformation and radial basis neural networks for classifying life threatening cardiac arrhythmias, Med. Biol. Eng. Comput. 37 (1999), pp. 566—573.

[5] F. Jager; I. Koren; L. Gyergyek Multiresolution representation and analysis of ECG waveforms, Computers in Cardiology Proceedings. Volume 23-26 (1990), PP.:547 – 550

[6] T. Linderberg Scale Space Theory in Computer Vision, Kluwer Academic Publishers. (1994), 440p.

[7] F. Mokhtarian, S. Abbasi, J. Kittler Efficient and Robust Retrieval by Shape Content through Curvature Scale Space, Int. Workshop on Image DataBases and Multimedia Search (1996), pp. 35-42.

[8] H. Strik, L. Boves Averaging physiological signals with the use of a DTW algorithm. In Proceedings of SPEECH'88, 7th FASE Symposium, Edinburgh, Book 3 (1988), pp. 883-890.

[9] Y.C. Chesnokov, D. Nerukh D., R.C. Glen Individually adaptable automatic QT detector. In Proc. Of Computers in Cardiology (2006) pp. 337-340.

[10] P. Laguna, R. Jané, P. Caminal Automatic detection of wave boundaries in multilead ECG signals: validation with the CSE database, In Proc. To Comput Biomed Res. Vol. 1 (1994), pp. 45-60.

Authors' Information

Natalie Belous *– Ph.D., head of ITLCVS laboratory, professor of Kharkov National University of Radio Electronics, Kharkov, Ukraine; e-mail: belous@kture.kharkov.ua*

Gleb Kobzar *– Researcher; Kharkov National University of Radio Electronics, Kharkov, Ukraine;*
e-mail: belous@kture.kharkov.ua