Evaluating Rest ECG Amplitude Changes Using the ECG Variability Contour Method

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Abstract

The "ECG variability contour" (EVC) method was studied with real life rest ECG.

Three 1-min long, 12-lead, rest ECG formed the data sets. Mean ECG complex was calculated for each data set, and subtracted from it and the other 2 data sets, forming 9 residue matrices. Residue matrix variables were: (1) EVC reflecting ECG variability (2) normalized cumulative sum (NCS) reflecting consistent amplitude changes, and (3) the number of points of the NCS lying outside EVC, which defined a significant ECG change.

1052 ECG leads (92 examinees) were analyzed. In 73% of leads the temporal distance between the data set and the subtracted mean ECG had an effect. <1 point (0.5%) of the NCS was located outside the EVC. Using the EVC method, it was demonstrated that consistent ECG amplitude changes may be accurately localized to the corresponding ECG component, and these changes were rare at rest.

1. Introduction

An alternative computerized method of ECG analysis was recently proposed by which ECG amplitude changes were compared with the variance of the ECG signal, instead of measuring absolute millivolt deviation [1-3]. Practically, 2 ECG data sets were compared (e.g. rest and stress), the mean rest ECG complex, <R-ECG>, was subtracted from both data sets, resulting in 2 residue matrices. The rest residue matrix provided a graphic measure of the variance of the ECG called: ECG variability contour (EVC), whereas the stress residue matrix provided 2 measures of ECG amplitude changes (from rest to stress). Hitherto, the EVC method was not used with real data. The stability of the method is examined here with real life rest ECG data. We investigated the relation between EVC and the measures of amplitude change and how both depended on selecting data sets Rj-ECG (j=1,2,3) and their means <Ri-ECG> (i=1,2,3).

2. Methods

2.1. Patients and ECG acquisition

Ninety-two consecutive examinees suspected of having ischemic heart disease were referred for a myocardial perfusion imaging scan. None of the examinees suffered chest pain during the rested state prior to the scan. All examinees gave their informed consent prior to participating in this study.

Standard 12-lead ECG was recorded using a PC-based system (PC ECG 1200, Norav Medical LTD, Kiryat Bialik, 27104, Israel,) at rest (supine position, prior to Dipyridamole administration). Device high, low, and mains interference filters were set of 0.05, 300 and 50-60 Hz. Signals were sampled at 500 Hz, and digitized at 12-bit.

2.2. ECG pre-processing procedures

ECG pre-processing was executed by a series of MATLAB (The Mathworks Inc., Natick, Mass) programs. Prior to analyzing ECG data, each lead underwent the following 4 steps: Artifact removal [4], determining a fiducial point for each ECG complex [5], baseline wander removal [1,4], and manual selection of points determining the components of the ECG complex [4].

2.3. ECG analysis

2.3.1. ECG data sets, complexes, mean ECG complex, and residue matrices

Standard 12-lead ECG was recorded for 5 minutes during rest, from which three 1-minute data sets were created R1-ECG, R2-ECG, and R3-ECG. Let N be the number of complexes in the 5-minute ECG, then

complexes forming R1-ECG, R2-ECG and R3-ECG were 10 to 70, N/2-30 to N/2+30, and N-70 to N-10, respectively. ECG complexes in each data set were organized in matrices aligned by the peak of the R wave. This enabled locating and studying the "f"-th element of the "g"-th ECG complex composing the data set. Figure 1 step 1, shows the 3 ECG data sets.

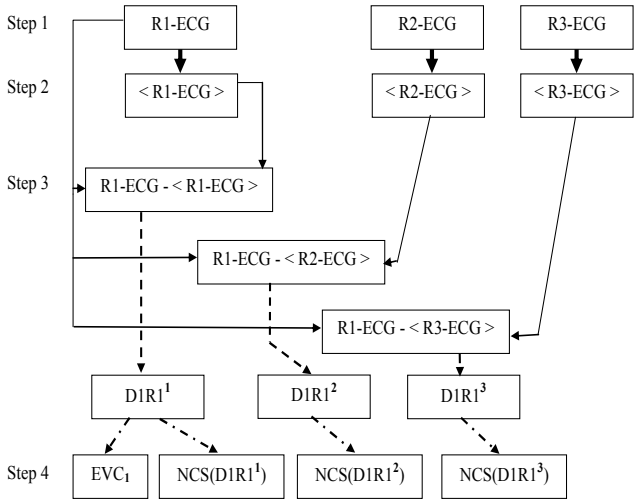

Figure 1 – Algorithm of ECG analysis

For each data set a mean complex, $<R_i\text{-ECG}>$, was calculated describing the "typical" morphology of the ECG complex in the set (figure 1 step 2). For example, let $ECG_{f,g}$ denote the "f"-th element in complex "g" in the ECG data matrix R1-ECG, then the mean element of R1-ECG was $<R1\text{-}ECG_f> = 1/n\ \Sigma_g\ ECG_{f,g}$ where g=1,…,n, (n= number of complexes in R1-ECG).

<Ri-ECG> (i=1,2,3) was subtracted from each ECG matrix Rj-ECG (j=1,2,3) resulting in the 3 "trivial" residue matrices denoted by $D1R1^1$, $D1R2^1$, and $D1R3^1$, where $D1Rj^1$=Rj-ECG–<Ri-ECG> and i=j (figure 1, step 3) and the other 6 residue matrices where i≠j. Constructing the 9 residue matrices was important for assessing how and to what extent <Ri-ECG> affected the calculated measures of the residue matrices. Figure 1, step 3 shows the 3 residue matrices constructed for data set R1-ECG only.

2.3.2. ECG Variability Contour

The standard deviation of $D1Rj^1$ (j=1,2,3) was calculated and ± twice that value defined a 2-dimensional space containing 96% of the residues (assuming residues were randomly and bell-shaped distributed). This 2-dimensional space was termed: "ECG variability contour", and denoted: EVC_k where k=1,2,3 (figure 1, step 4, left most box). To emphasize, EVC_k, was calculated only for the trivial residue matrices. The EVC served as a reference for the measures of ECG amplitude changes [1].

2.3.3. Normalized cumulative sum of the residue matrix – a measure of amplitude change

The residue matrix contained elements showing the difference between points "p" in each individual ECG complex composing the ECG data set and point "p" in <Ri-ECG>. Cumulatively summing the values of points "p" in the residue matrix and normalizing this sum by the number of summations, reflected the *consistency* of these differences. For example, let the differences between points "p" in the individual complexes composing a data set and point "p" in <Ri-ECG> derive from an arbitrary process, then, said differences obtain positive and negative values in an arbitrary fashion. Summing these differences would result in a value approaching zero. Normalizing the latter sum by the number of summations (according to the number of complexes in the set) would push the value further to zero.

To conclude, the NCS reflected *consistent* amplitude differences, where the contribution of outlier values was negligible because of averaging. The NCS of residue matrix $D1Rj^i$ was denoted by: $NCS(D1Rj^i)$ and shown for $D1R1^i$ i=1,2,3 in figure 1, step 4.

2.3.4. Percent variation of the area under curve of EVC and NCS($D1Rj^i$)

In figure 2, EVC is the space bounded by the thick upper and lower most lines. The area under curve of EVC, $AUC(EVC_k)$, is the area between the thick upper line and zero line (solid). AUC was calculated using a numerical, trapezoidal approximation of the integral of the curve. For each lead, $AUC(EVC_k)$ (k=1,2,3) were divided by the smallest value of $AUC(EVC_k)$ providing a ratio for comparison of AUCs (instead of absolute values). $AUC(NCS(D1Rj^1))$ equaled 0 (because the sum of points "p" in $D1Rj^1$ always equaled zero). It was expected that the greater the temporal distance between i (index of the mean complex, <Ri-ECG>) and j (index of ECG data set, Rj-ECG) was, the greater was the corresponding $AUC(NCS(D1Rj^i))$. Thus, $AUC(NCS(D1R3^1)) > AUC(NCS(D1R3^2)) > AUC(NCS(D1R3^1))=0$.

2.3.5. Number of points of NCS($D1Rj^i$) lying outside the EVC_k

The AUC(NCS(D1Rj^i)) did not allocate the difference between the NCSs to a specific component of the ECG. To this end, the number of points of NCS(D1Rj^i) (i=1,2,3) lying outside the EVC$_k$ (k=j) were summed for all leads and presented as a function of ECG component, and D1Rj^i k=j, with respect to the specific ECG component.

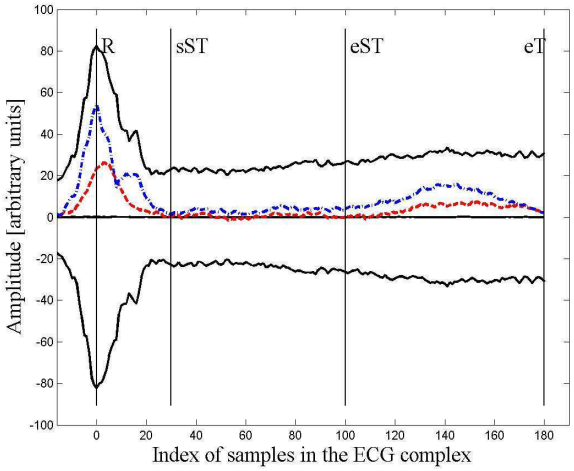

Figure 2 – The normalized cumulative sum of D1R1^i (i=1 (solid), 2 (dashed), 3 (dashdot)) all bounded within EVC$_1$ (thick lines). R, sST, eST and eT, show peak of R, beginning and ending of ST, and ending of T wave, respectively.

To emphasize, a point "p" of NCS(D1Rj^i) which laid outside EVC$_k$, actually represented a *consistent* amplitude difference between points "p" of the ECG data set, Rj-ECG, and point "p" of the mean complex <Ri-ECG>. It was arbitrarily defined that any point of NCS(D1Rj^i) lying outside EVC$_k$ (k=j) represented a significant amplitude change.

3. Results

92 examinees were recruited, 1052 leads analyzed (a mean of 11.4 leads per examinee). 346±100 complexes composed each ECG lead. 52 leads were not analyzed due to low quality signal.

The mean greatest and second greatest AUC(EVC$_k$) were 45.7% and 15.6% greater than the reference (smallest) AUC(EVC$_k$), respectively. AUC(EVC$_k$) didn't show a particular pattern, where for some k AUC(EVC$_k$) was consistently greater than AUC(EVC$_k$) for some other k.

For 751 leads (71.4%) the AUC(NCS(D1R1^3)) was greater than AUC(NCS(D1R1^2)) by a mean of 65%. For the minority of leads (28.6%) AUC(NCS(D1R1^2)) was greater than AUC(NCS(D1R1^3)) by a mean of 40.9%. A similar result was found for AUC(NCS(D1R3^1)) and AUC(NCS(D1R3^2)). These results show that in >70% of leads, when | i-j | = 2, the AUC(NCS(D1Rj^i)) was greater than that when | i-j | = 1.

For residue matrix D1R2, in 575 leads (54.7%) AUC(NCS(D1R2^1)) was greater than AUC(NCS(D1R2^3)) by a mean of 84.3%. In 45.3% of the leads, AUC(NCS(D1R2^3)) was greater than AUC(NCS(D1R2^1)) by a mean of 69.5%. For D1R2^i (i=1,2,3), the temporal distance between the mean complexes <R1-ECG> and <R3-ECG> and the ECG data set R2-ECG was shorter than it was for D1R1^i and D1R3^i. Specifically, | i-j | could only obtain the value 1. Figure 3 shows a 3-dimensional bar graph, where for each residue matrix (y axis) and each complex component (x axis), 3 bars depicted the sum of the points of NCS(D1Rj^i) (i=1,2,3) lying outside EVC$_k$ (z axis), for all 1052 leads. The complex component which had the maximum number of elements of NCS lying outside EVC was the T segment, with a maximum of 1.43 (1502/1052) points per lead. For the T component, the number of points of NCS(D1Rj^i) lying outside EVC$_k$ when | i-j | = 1 was 707, 717, 774, 628. When | i-j | = 2 the number of points increased to 1198 and 1502 (R1-ECG and R3-ECG, respectively). Analysis of the QRS component showed qualitative results similar to those of the T. The results for the ST segment were opposite to those for the QRS and T components. Namely, when | i-j | = 1, the number of elements of NCS(D1Rj^i) lying outside EVC$_k$ was greater than it was when | i-j | = 2. It is important to note that for a single lead, on the average, the number of points lying outside EVC was less than 1.

4. Summary and limitations

The goal was to evaluate the utility and stability of the EVC method as a tool for detecting ECG amplitude changes. It was a priori assumed that the three ECG data sets homogenously represented the rested state. It was shown that significant consistent amplitude changes during rest are rare, and the EVC method was stable for 5 minute long rest ECG signals. However, AUC(EVC$_k$) varied with time. Possible causes for the variance of elements of D1Rj^1 were: (1) external or physiological noise occurring at a specific part of the signal, (2) dynamics of the signal such as electrical alternans, and (3) misalignment of the ECG complexes in the data matrix due to consistent erroneous detection of fiducial point. Evidence supporting these mechanisms was not found. Thus, we cannot point to the causes underlying the variability of the EVC. Both measures of amplitude change, AUC(NCS(D1Rj^i)) and the number of points of

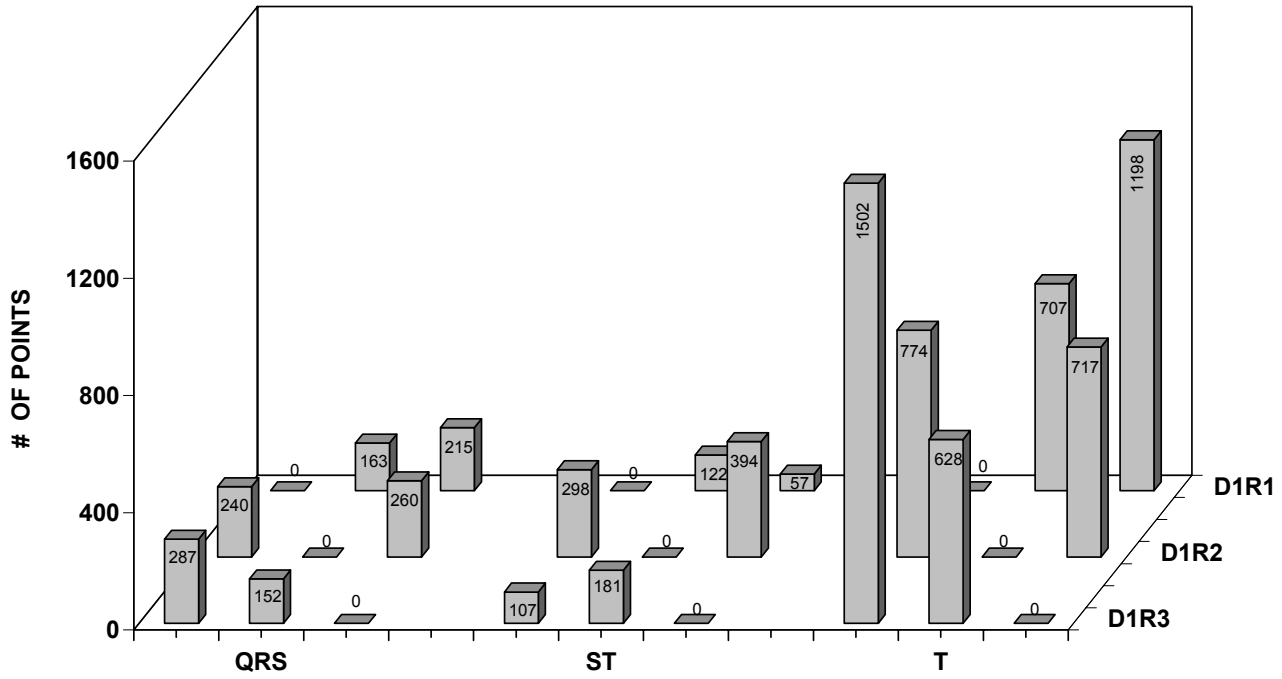

Figure 3 – Number of points of NCS (z-axis) lying outside EVC according to complex component (x-axis) and residue matrix (y-axis).

NCS(D1Rj) lying outside EVC_k demonstrated the same phenomenon, where their values usually increased as the temporal distance between <Ri-ECG> and Rj-ECG increased (as | i-j | increased).

We thought that this result was expected assuming signal varies with time. The time length of our data was roughly 5 minutes. The results obtained here show morphological difference between individual ECG complexes recorded at one time and a mean ECG complex recorded approximately 3 minutes earlier or later. This study didn't reveal how morphological difference of ECG complexes varies with data set size.

Figure 2 shows that the contour of NCS($D1R1^3$) is similar to that of NCS($D1R1^2$) however coarsely shifted upwards. This means that the greater AUC derived from a greater difference between each and every element of the individual complexes composing data set R1-ECG and the subtracted mean complex <R3-ECG>.

The fact that more amplitude variability was detected in the QRS than the ST component supported previous observation [4].

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