Calculating Optimal Virtual Lead from Multichannel ECG by Minimizing Morphological Beat-to-Beat Variability

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Abstract

A novel measure of the morphological beat-to-beat variation of signals derived from multichannel ECG is presented. It is used to find an optimal linear functional that maps the electrical activity of the heart into a single virtual lead in the sense of least beat-to-beat variability.

The results show that for each subject it is possible to find a virtual lead with less beat-to-beat variability compared to the standard ECG-leads. Furthermore, the new measure gives precise quantitative information about the beat-to-beat variability in the standard lead set.

1. Introduction

It can be argued that the first step in electrocardiogram (ECG) processing is selecting a suitable representation for the data. This choice guides the placement of the electrodes and the derivation of the actual leads as functions of the potentials at the measurement sites.

The problem of selecting a suitable set of multiple leads has been studied especially in the viewpoint of what reduced lead set produces the best reconstruction of the body surface potentials (e.g. traditional 12-lead ECG) or one that maximizes the information content of the lead set [1-3].

In ambulatory measurements, simultaneous processing of several individual measurement channels with an embedded device is often infeasible. Therefore, it is often required that either the system must restrict to work on a single lead or map the measured leads into a virtual single channel signal that is used in later processing stages.

For some applications, it is desirable to have a signal that retains as much of the original information as possible despite the fact that this can lead to more heterogeneous morphology, e.g. due to respiration and movement artifacts. In other applications, we would like the signal to be as consistent as possible showing little beat-to-beat variability. For instance, the latter approach could be especially beneficial in ECG segmentation, since the quality of the segmentation can have a profound effect on the quality of later analysis [4, 5].

In this paper, we present a preliminary study that quantifies the morphological beat-to-beat variability of virtual leads calculated from multichannel ECG when using a linear model.

The rest of the paper is organized as follows. First, we describe the methods and the data in section 2. Then, the results are presented in Section 3. Finally, discussion and conclusions are presented in section 4.

2. Methods and materials

2.1. Constructing the virtual signal

The electric field generated by heart can be modeled with good accuracy using a dipole model in which the strength and orientation of the source vary in time [6]. This behavior can be captured using the electric heart vector (EHV) which is a mapping $\boldsymbol{h}: \mathbb{R} \rightarrow \mathbb{R}^3$ such that

$$\boldsymbol{h}(\boldsymbol{t}) = [\boldsymbol{x}(\boldsymbol{t}) \quad \boldsymbol{y}(\boldsymbol{t}) \quad \boldsymbol{z}(\boldsymbol{t})]^{\boldsymbol{T}}$$

where x, y, z are the real-valued component functions that represent the source strength with respect to the corresponding axes at each time instant.

Using the EHV model, the task of finding a derived lead can be formulated mathematically. We seek a functional $A_t: \mathbb{R}^3 \rightarrow \mathbb{R}: \boldsymbol{h}(t) \longmapsto (A_t\boldsymbol{h})(t) = v(t)$ with suitable properties.

In order to obtain a meaningful signal, we must fix the sense in which the functional A_t is to be sought. To narrow the scope, we restrict to time-invariant functionals $A_t = A$ in this paper. In addition, we require that A is a linear functional.

According to the Riesz Representation Theorem for finite dimensional vector spaces [7], a linear functional operating on $\boldsymbol{h}$ can always be expressed as

$$(A\boldsymbol{h})(t) = \boldsymbol{w}^T\boldsymbol{h}(t)$$

where the constant vector $\boldsymbol{w} = [w_1 \quad w_2 \quad w_3]^T \in \mathbb{R}^3$ is often called a *lead vector* on which the EHV can be interpreted to be projected on. Without loss of generality, we can further restrict $\boldsymbol{w}$ to be a unit vector.

Lead switching/selection algorithms [8] can be seen as examples of time-variant functionals where A is restricted to linear form and at each time instant t, and $\boldsymbol{w}$ to be selected as a row vector of the Dower matrix [9]. In addition, some specific non-linear functionals have also been used. For example, the root-mean-square (RMS) of the measured leads has been found useful [10].

It should be noted that the presentation is not restricted to the EHV model only, but any other multidimensional presentation of the electrical activity may used as well.

2.2. Optimality of the virtual signal

In order to select A optimally, we must device means to measure the optimality. Hence, consider a sampled version of the derived signal $(A\boldsymbol{h})(t)$ during a beat $t \in [a_i, b_i]$. For each beat from a totality of N beats, let the samples be collected into a vector $\boldsymbol{x}_i \in \mathbb{R}^M$, $i = 1, \dots, N$, which is zero padded in case the beat is shorter than the predetermined duration of M samples.

Then, let us define the mean shape of the beat as

$$\widehat{\boldsymbol{\mu}} = \arg\min_{\boldsymbol{\mu}} \frac{1}{N} \sum_{i=1}^{N} d_\tau^2(\boldsymbol{x}_i, \boldsymbol{\mu})$$

where

$$d_\tau(\boldsymbol{x}_i, \boldsymbol{\mu}) = \min_\tau \| \tau \circ \boldsymbol{x}_i - \boldsymbol{\mu} \|$$

is the distance between the mean shape candidate $\boldsymbol{\mu}$ and the ith beat $\boldsymbol{x}_i$ when they are aligned in time as close to each other as possible using the cyclic interpolation operator τ. For a more general multidimensional exposition of these concepts, please refer to [11].

Finally, let us define the objective function

$$J(\boldsymbol{w}) = \frac{\sum_{i=1}^{N} d_\tau^2(\boldsymbol{x}_i, \widehat{\boldsymbol{\mu}})}{\sum_{i=1}^{N} var(\boldsymbol{x}_i)}.$$

where $var(\boldsymbol{x}_i) = \sum_{j=1}^{M} \left(x_{ij} - \overline{x_{ij}}\right)^2$ represents the AC-energy of the derived signal during the beat. Clearly, the objective function is non-negative. Moreover, it possesses several other desirable properties. First, it is invariant to isotropic scaling, i.e. $J(\boldsymbol{w}) = J(s\boldsymbol{w})$ for all $s \neq 0$. Second, the larger the value of the objective function is, the larger the beat-to-beat variation in the derived signal is. Third, the lesser the signal energy is, the higher the value of the objective function is. The objective function is also continuous and smooth. Hence, the minimum ($\min_{\boldsymbol{w}} J(\boldsymbol{w})$) can be sought with standard numerical methods.

2.3. Data

ECG measurements were gathered in different body positions and respiration depths. In total, there were 25 healthy volunteers between 19 to 53 years old. Ten of them were females and 15 of them were males.

The measurements were made with RAFE lead system [12] using a Medilog AR12 Digital ECG Recorder (Oxford Instruments, Eynsham, UK). The amplitude resolution of the three stored Frank leads that are proportional to the EHV [13] was 16 bits at sampling rates 1024 Hz (X), and 512 Hz (Y, Z). Afterwards, the X channel was resampled at a rate of 512 Hz.

The recordings lasted for 18 minutes per person. In the course of the measurement, body position and respiration depth was controlled by the instructor who gave orders at predefined time instants seconds before each action were to take place. A timer was used to initiate the execution an exact time instant. For a detailed measurement protocol, please see [11].

After measurements, the beats were extracted using our implementation of the shift invariant wavelet transform based segmentation algorithm presented in [14, 15]. As a post-processing step for each beat, a linear trend was subtracted from each of the Frank leads to remove baseline wander.

3. Results

For comparison, the beat-to-beat variability of the aVL lead for the first subject is represented in Fig.1. At each instant, a curve shows the corresponding percentile distribution of data points, when all the beats have been aligned on top of each other optimally. Percentiles ranging from 10 % to 90 % with 10 % intervals are used.

The beat-to-beat variability in the optimal lead using $\widehat{\boldsymbol{w}} = \arg\min_{\|\boldsymbol{w}\|=1} J(\boldsymbol{w})$ is shown in Fig. 2 for the first subject. Overall, the aVL lead in Fig. 1 has 54 % more variation compared to this optimal location (see Table 1).

When $\boldsymbol{w}$ is a unit vector in $\mathbb{R}^3$, it belongs to the unit sphere that can be parameterized with two angles: the elevation $\theta \in [-\pi/2, \pi/2]$, and the azimuth $\phi \in [-\pi, \pi]$. We use three axes, where X-axis points forward out of the chest, Y-axis points to the left, and Z-axis points up towards the head. The elevation θ is the angle between the direction vector and the XY-plane, counting

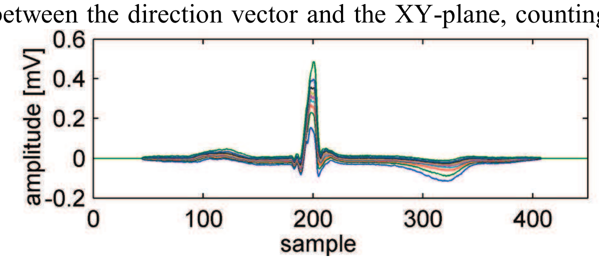

Figure 1. Beat-to-beat variation in the aVL lead of the standard 12-lead ECG for the first subject.

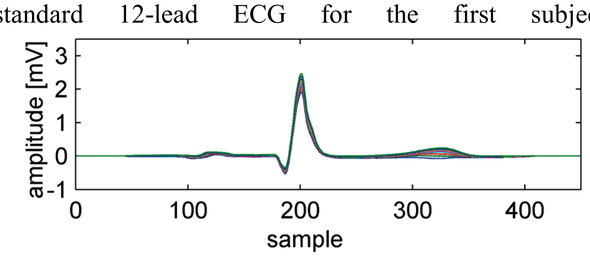

Figure 2. Beat-to-beat variation in the optimal virtual lead for the first subject.

positive towards the positive Z-axis. The azimuth ϕ is the angle between the projection of the direction vector on the XY-plane and the X-axis with the counter-clockwise convention for positive angle. Due to scale invariance, the symmetry $J(\boldsymbol{w}) = J(-\boldsymbol{w})$ becomes $J(\phi, \theta) = J(\phi \pm \pi, -\theta)$ in the spherical coordinate system.

Fig. 3 shows the objective function $J(\phi, \theta)$ as a contour plot for each person in the spherical coordinate system ordered by person number first from left to right, and then top to bottom. The function takes on a given constant value on each line. Minima of the objective function and the locations of the standard leads according to the Dower matrix are also shown. The symmetry property of the objective function is evident from the contour plots. It can also be seen that in many cases some of the standard leads show significant beat-to-beat variation according to the objective function.

Table 1 compares the amounts of variation at the standard leads to that of the minima, i.e. shows the values $J(\boldsymbol{w_i}) / \min_{\boldsymbol{w}} J(\boldsymbol{w}) \times 100$ %, where $\boldsymbol{w_i}$ is a row vector of the Dower matrix.

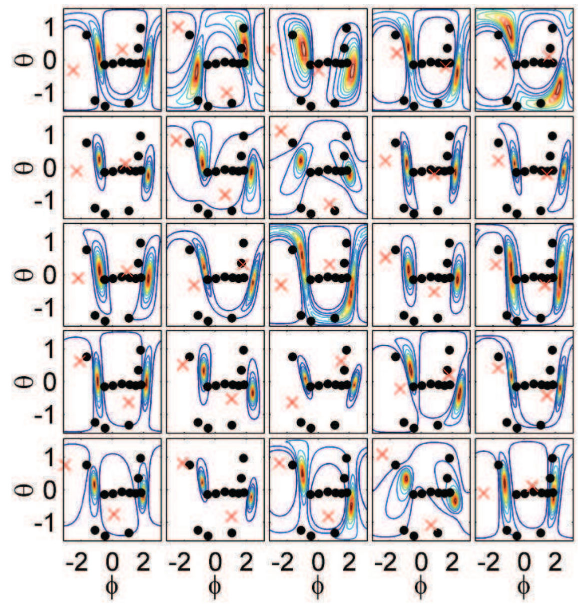

Figure 3. Contour plots of the objective function. The dots (●) represent the lead locations of the standard ECG, and the crosses (×) represent the optimal locations.

Table 1. The amounts of variation at the standard ECG leads relative to the optimal virtual lead in per cent units.

Person	I	II	III	aVR	aVL	aVF	V1	V2	V3	V4	V5	V6
1	135	477	206	239	154	308	304	115	103	112	137	214
2	630	145	418	127	823	242	200	157	161	178	237	575
3	447	273	196	664	279	164	475	102	183	316	490	788
4	114	463	234	131	166	342	398	163	126	110	101	107
5	104	944	293	228	174	524	285	140	113	104	103	111
6	125	181	158	143	142	172	297	123	102	102	115	166
7	181	377	339	164	278	381	563	244	185	150	135	169
8	264	111	149	125	180	129	168	167	182	202	248	446
9	176	368	311	158	243	380	361	134	103	103	131	295
10	111	335	202	136	154	265	1561	195	126	107	100	107
11	128	198	152	159	136	173	438	139	104	102	120	196
12	100	502	149	207	118	214	1874	241	145	117	106	115
13	138	1110	287	252	180	561	242	116	102	108	132	234
14	169	212	228	146	208	234	584	155	111	110	133	232
15	143	440	332	115	217	559	1009	277	148	106	107	233
16	177	303	373	121	281	424	272	138	114	109	124	251
17	208	253	366	129	328	343	778	212	127	112	132	243
18	103	119	102	145	101	106	325	123	105	101	106	134
19	102	381	176	163	131	251	728	201	133	112	104	107
20	135	689	322	121	217	500	787	222	148	118	107	138
21	334	207	284	176	314	253	125	125	147	177	246	659
22	140	179	176	112	164	184	337	159	134	123	122	142
23	237	380	402	150	338	439	223	148	143	146	167	277
24	277	111	167	148	204	139	166	148	180	216	266	369
25	312	287	322	256	327	310	155	110	101	114	200	1071

4. Discussion and conclusions

We have presented a novel way of measuring the beat-to-beat variation of signals derived from ECG in a general setting. In particular, we have focused on finding the optimal linear functional that maps the electrical activity of the heart into a single virtual lead in the sense of least beat-to-beat variability. According to the results (Table 1), some of the precordial leads (on the chest) are often close to optimal, but individual variations are large.

The main advantage of the new method is the scale invariance compared to standard RMS-type measures that typically show little variation in leads with lower signal levels, and larger variations with higher signal levels. In this respect, our method reveals the intrinsic variability of the signal irrespective of scale. It can be argued that this type of approach is favourable in comparison to direct application of methods that maximize the information content, such as entropy or variance, as they can lead to the inclusion of unwanted information sources and excessive beat-to-beat variation.

A disadvantage of the method is that the objective function does not differentiate a source of the beat-to-beat variability from another. The source may be anything from e.g. perspiration, respiration, movement artifacts or electromyographic noise to actual changes in the heart. Therefore, the method is sensitive to the selection of the data. The very same property, however, makes it very well suited to ambulatory conditions in which situations can change rapidly.

The method can be used to guide the electrode placement. Naturally, a direct measurement at the optimal location can be impractical, e.g. due to a local source of electromyographic noise. Nonetheless, the optimal signal can be derived from leads at more advantageous locations. This can be accomplished already in the analogue stage of the measurement device with little cost.

The methods presented can be expanded in a number of directions. For example, the requirements imposed on the functional can be relaxed by allowing it to vary in time and/or be non-linear. What is more, many other types of distance measures can be explored to redefine the objective function suitably. Further, an online version of the method could be applied to grid type ECG, e.g. in sensory shirts, to fuse information measured from a multitude of locations forming a stable signal even though the contact and placement of the electrodes vary.

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