Visual Analysis of ECG Sequences on Variant Maps

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Abstract This chapter presents the variant measurement based on the variant logic, which uses the ECG sequence as the signal source, and outputs the variant maps of ECG sequences. It provides a supplementary study for ECG detection. Samples of ECG signal are collected from the First People's Hospital of Yunnan Province. Under variant maps, main parameters of various interval values are checked and corresponding maps are illustrated.

Keywords Arrhythmia · Visualization · ECG sequences · Variant map

1 Introduction

The world is concerned about the cardiovascular disease [1]. Mainly relying on the detection of ECG signals to promote research on related issues of cardiovascular diseases. The electrocardiogram represents cardiac function and graphic signals [2], which is an important means of diagnosing abnormal cardiac activity.

ECG signals are the product of a wide range of clinical ECG techniques. In recent years, research methods for ECG signals have made significant progress, such as using machine learning [3], neural network, clustering [4], partial fractal dimension [5], wavelet transform [6], and other methods to classify the detection of arrhythmia. The most typical representative of the emerging ECG research method is ECG scatter gram [7–9].

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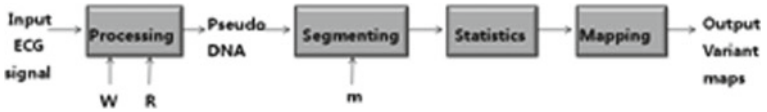


Fig. 1 The overall structure of the variant map for ECG

The variant method is an emerging technique for dealing with spatial changes in signal phase. Since the 1990s, the application of the variant method in processing binary image classification and transformation [10, 11] had been proposed, and the variant method has been perfected until now [12, 13]. Variant method is applied to different data samples: quantum sequences [14, 15], random sequences [16], non-coding DNA [17–19], bat echo signals [20], and electrocardiographic signals [21, 22], and effective research results have been obtained in these samples.

This chapter is a further study of the use of variant measurements in the detection of ECG sequences. The sample ECG signals are provided by the First People's Hospital of Yunnan Province. In this chapter, two groups of signals are used: normal ECG signal and abnormal ECG signal groups. In the second part of this chapter, we describe variant map for ECG. Showing sample results and making a brief analysis in the third part, the last part is the summary of the chapter.

2 Variant Map for ECG

Variant map for ECG is composed of six parts: Input, Processing, Segmenting, Statistics, Mapping, and Output. Figure 1 is the overall structure of the variant map for ECG, which specific content about each part in the following description:

A. *Input Part*

Testing ECG signals are provided by the hospital as a data source. Let ECG signals be p with N elements.

$$p = \{p_0, \ldots, p_{N-1}\}$$

B. *Processing Part*

In processing part, a multivalve ECG signal sequence will be transformed into a four-valued pseudo-DNA sequence.
Input: the ECG sequence

$$p = \{p_0, \ldots, p_{N-1}\}$$

Parameters: W sliding window value; R interval value.
Output: a four-valued pseudo-DNA sequence

$$q = \{q_0, \ldots, q_{N-1}\}$$

Processing:

Let $\overline{p_i}$ be an average value; r be a range value; t_i be a conversion value. Three values are calculated in the equations:

$$\bar{p}_i = \sum_{i=0}^{N-1} \frac{p_i}{W}$$

$$p_{\max} = \max\{p_i\}, 0 \le i < N-1$$

$$p_{\min} = \min\{p_i\}, 0 \le i < N-1$$

$$r = (p_{\max} - p_{\min}) * \frac{R}{2}$$

$$t_i = \frac{2(p_i - \bar{p}_i)}{r * R}$$

Transforming rules: $0 \le i < N-1$

$$\text{if } t_i > R > 0 : q_i = A; \text{ if } 0 < t_i < R : q_i = G;$$

$$\text{if } 0 > t_i > -R : q_i = C; \text{ if } 0 > -R > t_i : q_i = T;$$

C. *Segmenting Part*

Input: $q = \{q_0, \ldots, q_{N-1}\}$.

Parameters: m is a segment value.

Output: $Q = \{Q_0, \ldots, Q_j, \ldots, Q_{M-1}\}, 0 \le j < M$; M is segments and $N = m * M$.

Processing: the j-th element in $Q = \{Q_0, \ldots, Q_j, \ldots, Q_{M-1}\}$;

$$Q_j = \{q_{j*m}, \ldots, q_{j*m+i}, \ldots, q_{j*m+m-1}\}, \ 0 \le i < m, 0 \le j < M.$$

D. *Statistics Part*

Input: $Q = \{Q_0, \ldots, Q_j, \ldots, Q_{M-1}\}, 0 \le j < M$

Output: $S = \left\{S_j^A, S_j^C, S_j^G, S_j^T\right\}, 0 \le j < M$

S_j^A is value of the number of A element in Q_j

S_j^C is value of the number of C element in Q_j

S_j^G is value of the number of G element in Q_j

S_j^T is value of the number of T element in Q_j

E. *Mapping Part*

Selecting a pair of two elements in $S = \left\{S_j^A, S_j^C, S_j^G, S_j^T\right\}$, $0 \leq j < M$, as a mapping object. This chapter selects $\left(S_j^C, S_j^G\right)$. S_j^C is corresponding to the X-axis and S_j^G is corresponding to the Y-axis. All M pairs are mapping to the 2D map as output.

F. *Output*

The results of the mapping are output in the form of 2D variant maps.

3 Sample Results and Brief Analysis

Visualization results of ECG signal obtained by variant map for ECG show that the morphological features of ECG signals have regular changes. Sample results are illustrated and a brief analysis is described.

A. *Data Source Description*

The ECG signals in this chapter are provided by the First People Hospital of Yunnan Province. The ECG signals contain a total of 202,626 cases. There are 104,742 normal cases and 97,884 abnormal cases of records. For this experiment, 97,884 normal cases and 97,884 abnormal cases were selected.

Since ECG signals have multiple attributes, this chapter chooses the attributes of the P wave samples to be processed. Figure 2 is the sample of part of abnormal ECG data source.

B. *Visualization Features*

Using the variant map for ECG, multiple maps can be generated.

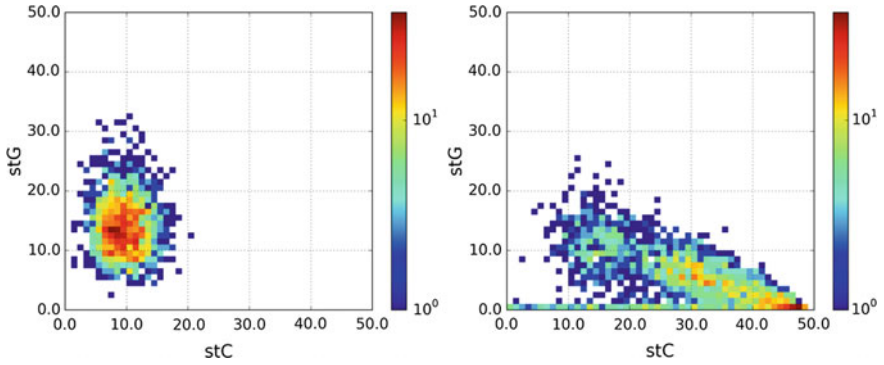
The interesting finding is that the changes of the parameters affect the spatial characteristics and phase changes of the maps.

Overall in Fig. 3, two 2D maps are illustrated for two normal/abnormal maps, parameters are $W = 24$, $R = 0.95$, $m = 50$. X and Y are $\left(S_j^C, S_j^G\right)$ $0 \leq j < M$, the ECG variant map shows the regular characteristics. In Fig. 3a, a normal map for P wave is an oval. In Fig. 3b, an abnormal map for P wave is a stick.

In Fig. 4, a list of normal maps for P wave on parameters $R = \{0.6, 0.72, 0.84, 0.96, 65, 1.08, 1.2\}$. When the parameter R increases, the feature of relevant maps has a nonlinear displacement along the top right corner of the image.

STUDYINSTANCEUID	CONCLUSION	QRSDZ	RS_WIDTP	WIDTHR	WIDTHT	WIDTH	QTC	P
GRKS2014042900001	窦性心动过缓、ST-T改变	89	80	-43	89	0	465	110
JZNK2S2015052100019	窦性心动过缓、ST-T改变	33	86	68	33	0	430	96
JZNK2S2015042400005	窦性心动过缓、ST-T改变	-9	84	31	-9	0	459	94
JZNK2S2015060100008	窦性心动过缓、ST-T改变	17	84	-14	17	0	423	118
JZNK2S2015061300006	窦性心动过缓、ST-T改变	48	76	-61	48	0	480	92
JZNK3S2015083000004	窦性心动过缓、ST-T改变	16	88	-47	16	0	454	90
JZNK3S2015072900012	窦性心动过缓、ST-T改变	56	94	-4	56	0	472	120
JZNK3S2015072700025	窦性心动过缓、ST-T改变	32	82	31	32	0	430	98
JZNK3S2015091500013	窦性心动过缓、ST-T改变	67	82	90	67	0	460	134
JZNK3S2015092600013	窦性心动过缓、ST-T改变	8	92	4	8	0	451	82
JZNK3S2015100600001	窦性心动过缓、ST-T改变	-35	128	-58	-35	0	514	102
JZNKS2014091500001	窦性心动过缓、ST-T改变	90	88	-13	90	0	419	74
JZNKS2014101000001	窦性心动过缓、ST-T改变	36	92	30	36	0	498	80

Fig. 2 The sample of part of abnormal ECG data source



(a) A normal map for ECG P wave (b) An abnormal map for ECG P wave

Fig. 3 The example of normal and not ECG variant map

In Fig. 5, a list of abnormal maps for P wave on parameters $R = \{0.6, 0.72, 0.84, 0.96, 65, 1.08, 1.2\}$. When the parameter R increases, the feature of relevant maps has a nonlinear displacement along the top right corner of the image.

Comparing with Figs. 4 and 5, differences between normal and abnormal map features.

4 Summary and Prospect

Electrocardiogram (ECG) detection is the key to clinical diagnosis of heart disease and has important clinical value. At present, the automatic analysis function of dynamic ECG detection is not satisfactory. There are also problems that the features of waveform lesions are small and cannot be marked, and even the characteristics of lesions are neglected. Therefore, excavating the effective information existing in the massive ECG signal can avoid the blind area of ECG analysis to some extent, which has certain application value.

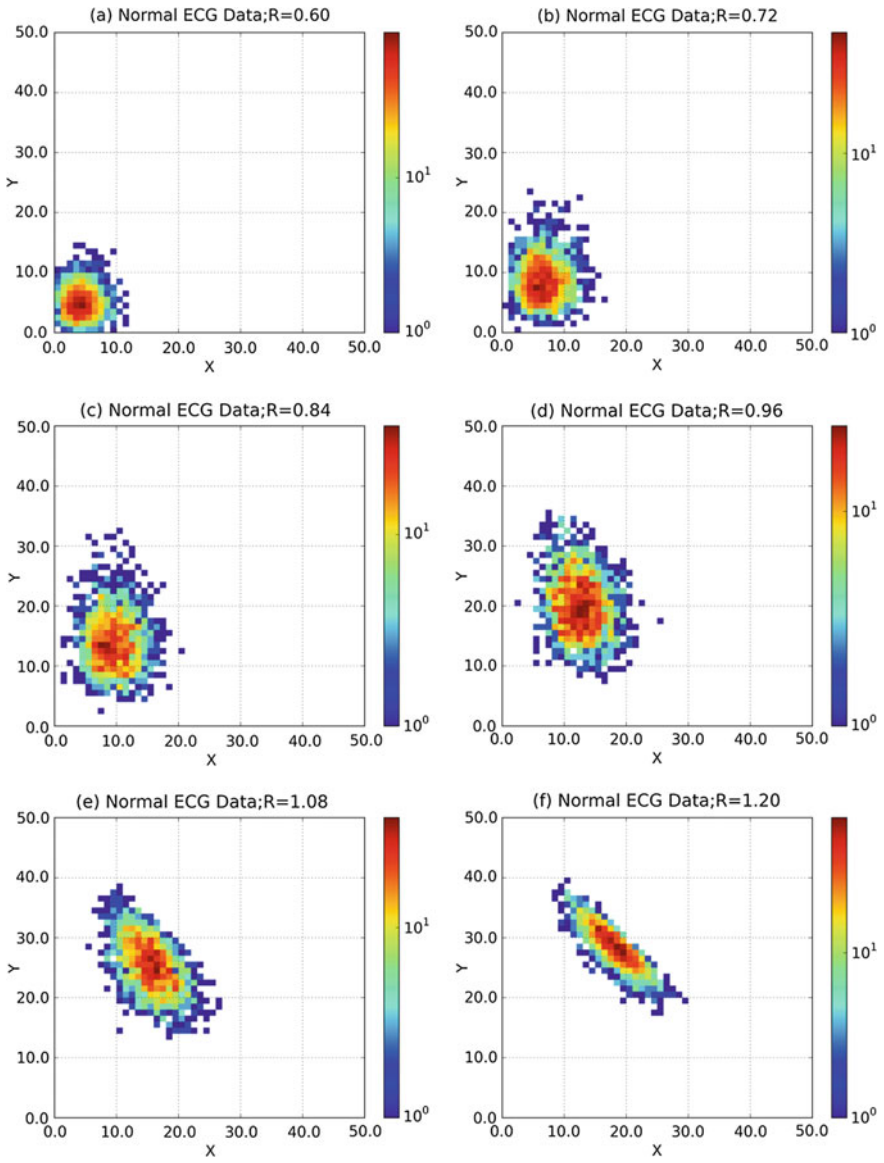


Fig. 4 A list of normal maps for P wave on parameters $R = \{0.6, 0.72, 0.84, 0.96, 65, 1.08, 1.2\}$; **a–f** maps on $R = \{0.6, 0.72, 0.84, 0.96, 65, 1.08, 1.2\}$

This chapter presents a new scheme of statistical distribution, variant map for ECG. This method can process massive ECG data sequences as 2D maps with visual characteristics. The sample results show classification of arrhythmia characteristics

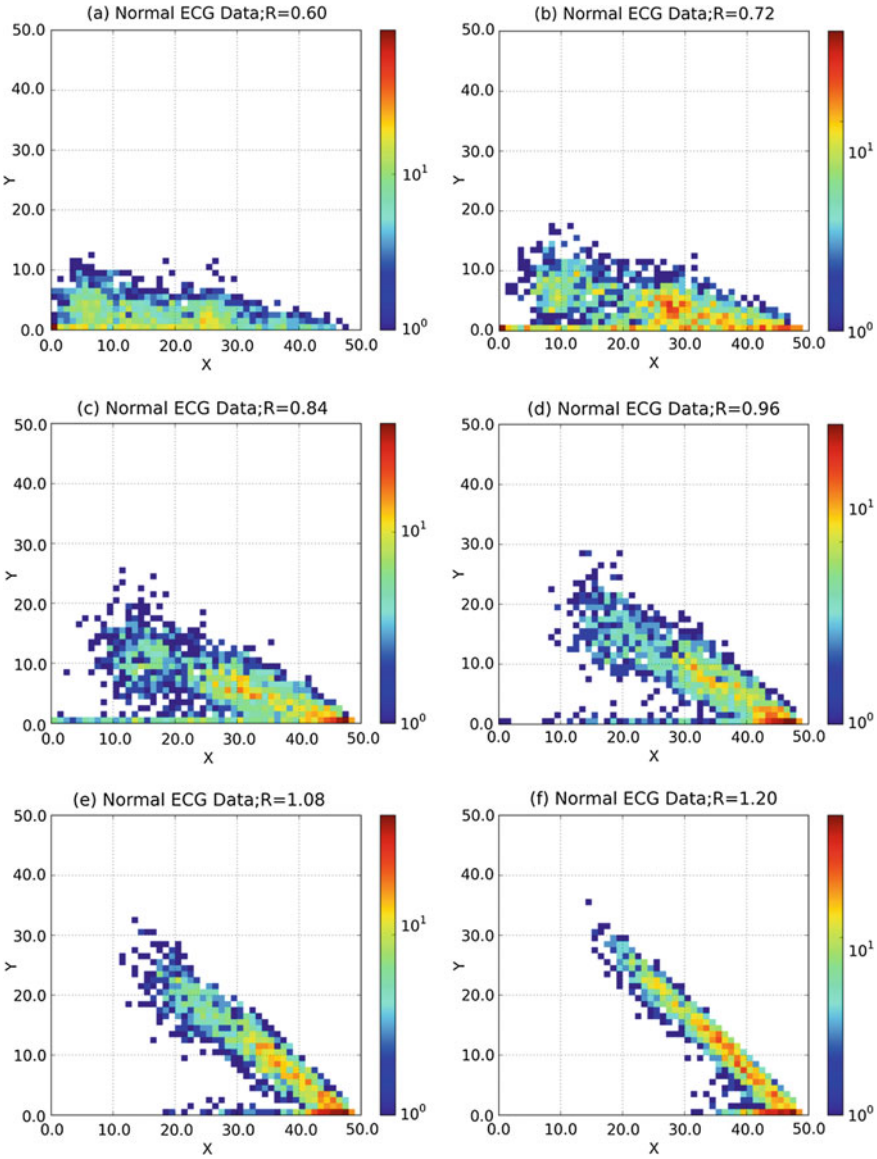


Fig. 5 A list of abnormal maps for *P* wave on parameters $R = \{0.6, 0.72, 0.84, 0.96, 65, 1.08, 1.2\}$; **a–f** maps on $R = \{0.6, 0.72, 0.84, 0.96, 65, 1.08, 1.2\}$

to identify the normal ECG signals and abnormal ECG signals significantly different. Further explorations and more experiments are required.

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