Cardiac Arrhythmia Interpretation System
Based on Blackboard Model

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Abstract: A prototype CAIS (cardiac arrhythmia interpretation system) based on blackboard model is presented. The issue of automatic electrocardiogram analysis is addressed firstly. The idea of bi-directional interaction is led into CAIS, which makes the system run in a kind of way rather close to human mode of thinking. The process of PVC (premature ventricular contraction) diagnosis in CAIS is described to illustrate the effectiveness of the system.

Keywords: Electrocardiogram (ECG), Cardiac arrhythmia, Signal interpretation, Blackboard system.

1. Introduction
The ECG is measured by electrodes placed on the surface of the body, which records the potential differences between different points of the surface generated by cardiac implies. It is the most important basis for diagnosing arrhythmia and myocardial infarction. With the development of Holter system transferred by telephone line and ECG telemeter & monitor system recently, requirements for robust automatic real-time ECG interpretation system are becoming increasingly urgent.

However, many defects still exist in the existing automatic ECG analysis system compared with ECG human experts. First, the knowledge bases in those systems are set up only basing on the mastered knowledge, while human experts can accumulate their experience gradually by means of practice. As the wave shape of ECG is different for different subjects and even for different beats of the same subject, limited number of rules can not describe all the possible features of wave shapes. The expert system should have automatic knowledge acquisition ability. Second, most of those expert systems are driven according to the rules of procedural programming. While experts' inference is complexly opportunistic and wholly modifiable in response to the scene change. No definite direction can be identified in the control flow of the expert operations. Information and data are used both in top-down and bottom-up fashion according to the current status of the interpretation. In order to make up for the second defect, the system should be developed in an environment that can support opportunistic inference.

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Blackboard model is the most used artificial intelligence architecture for sensor interpretation and related problems now. The concept of a blackboard model originated with the Hearsay-II speech understanding project [1]. A blackboard model is distinguished by three major characteristics: Problem solving is performed by cooperating KSs (knowledge sources); The KSs interact anonymously using a shared, structured database called blackboard; and problem solving is directed by a flexible control component that is separate from the KSs [2].

CAIS (cardiac arrhythmia interpretation system) based on blackboard model is just a prototype system for ECG interpretation. It uses a kind of neural network-fuzzy ARTMAP to extract fuzzy rules from training inputs directly, which are corresponding to experts' experience perfectly [3-4]. At the same time, the system is developed basing on a kind of blackboard model expert system shell-GBB (Generic Blackboard Builder). While in blackboard model, problem solving is directed by a flexible control component that is separate from KSs. The control flexibility inherent in the blackboard approach encourages an opportunistic approach to problem solving, because problem-solving activities can be quickly refocused as new information is uncovered. Furthermore, blackboard model can integrate numerical and symbolic data representations in a unique knowledge base. Therefore, algorithmic and inferential processes cooperate in the problem-solving activity and are interlaced with each other, which is rather close to the mode of human thinking [5-6]. So CAIS can resolves those problems mentioned above rather successfully.

The idea of bi-directional interaction between signal processing and interpretation is also led into the system, which means that front-end signal processing is dynamically modifiable in response to the need to re-
analyze data and can decrease the blindness in signal processing methods’ and control parameters’ choices [7].

A test-bed presented here is just try to diagnose PVC (premature ventricular contraction) beats from normal ones. Preliminary results of the system to data in MIT/BIH Arrhythmia Database confirm the effectiveness of the system.

2. ECG Signal Interpretation

Signal analysis is principally quantitative and only refer to basic event detection. However, signal interpretation means a more qualitative, context-dependent evaluation of the entire signal. A diagnosis system makes its diagnosis based on the patient history and the results of data obtained from laboratory tests.

Experts in ECG domain usually read ECG from left to right in two or three even twelve channels. They can immediately focus their attentions on several important pieces of duration in ECG. Applying their experience, they can achieve some partial conclusions soon. And after the whole ECG having been gone through, partial conclusions are combined into a final one.

That procedure can be simulated in signal processing domain and artificial intelligence domain in such a way: signal detection → feature extraction → single cycle diagnosis → contextual diagnosis → final diagnosis.

Signal detection is to identify each beat from the other of the signal with noise. As R-peak has high amplitude and frequency, it can not be distorted by noise usually. So R-peaks are always detected firstly in all kinds of methods. P-peaks and T-peaks are detected basing on the position of R-peaks, which has already been determined.

Feature extraction means to get visual evidence that the experts can obtain by means of skimming through the signal. They need to determine whether each parameter of the beat is over the limit or not. Those parameters include the height, width of P-wave, QRS complex and T-wave, and the intervals between them.

Single cycle diagnosis includes: atrial premature depolarization, atrial ectopic depolarization, atrial escape, sinus slowing, normal ventricular premature depolarization, junctional escape, ectopic ventricular premature depolarization, ventricular escape and ventricular fusion. Each atrial depolarization is further characterized as conducted or nonconducted, conducted with AV delay and/or conducted with normal or aberrant ventricular depolarization. Each normal or ventricular ectopic depolarization that is not proceeded but followed by an atrial depolarization is further characterized as occurring with or without retrograde atrial activation.

Single cycle diagnosis of the most current cardiac cycles is incorporated to drive a contextual diagnosis. Contextual diagnosis include sinus, atrial, junctional or idioventricular bradycardias; first-degree and second-
3. Blackboard-based System Architecture

The knowledge base of the system is divided into five kinds of knowledge source: Signal Processing (SP) knowledge source, Reprocessing (RP) knowledge source, Discrepancy Detection (DDC) knowledge source, Differential Diagnosis (DDF) knowledge source and Signal Interpretation (SI) knowledge source. Knowledge is represented as algorithm models (in SP knowledge source) or rules (in other knowledge source). So the activities of KSs are algorithms performance or rules execution (Fig. 1).

The control panel is compose of problem solving model, which is a summary of the current interpretations and the source of uncertainties associated with each one's supporting hypotheses, and planner, which maintains control using control plans and focusing heuristics.

4. Test-bed

The following discuss is upon PVC recognition problem. So it is only expected to reach a contextual diagnosis and the final diagnosis is not discussed here. As multi-level inference is not necessary for PVC recognition, the blackboard can be just divided into two levels: SP output level, which includes WT output sub-level, R-peak position sub-level, QRS-complex features sub-level, and the conclusion level.

4.1. SP Knowledge Source

Algorithm I: nonorthogonal WT based on Mexican hat function implemented according to A Trous algorithm [9]:

\[
\begin{align*}
x^{r+1} &= (g * x^r)_{s_{\min} \leq i \leq s_{\max}} \\
w^r &= \left( g * x^r \right)_{s_{\min} \leq i \leq s_{\max}} \\
\end{align*}
\]

Parameter 1: \( s_{\min} \) is the smallest scale, \( 0 \leq s_{\min} \leq 5 \), initialized by 0;
Parameter 2: \( s_{\max} \) is the biggest scale, \( 0 \leq s_{\max} \leq 5 \), \( s_{\min} \leq s_{\max} \), initialized by 3;

Algorithm II: Average Lipschitz exponent \( \alpha \) over WT domain.

\[
\alpha_j = \log_2 \left| w^{j+1}(x_{j+1}) \right| - \log_2 \left| w^j(x_j) \right|
\]

\[
\bar{\alpha} = \frac{1}{s_{\max} - s_{\min} + 1} \sum_{j=s_{\min}}^{s_{\max}} \alpha_j
\]

Parameter 1: \( s_{\min} \) is the smallest scale, \( 0 \leq s_{\min} \leq 5 \), initialized by 1;
Parameter 2: \( s_{\max} \) is the biggest scale, \( 0 \leq s_{\max} \leq 5 \), \( s_{\min} \leq s_{\max} \), initialized by 2;

degree AV block; atrial bigeminy, atrial trigeminy, atrial couplet, ventricular bigeminy, ventricular trigeminy, ventricular couplet, atrial tachycardia atrial flutter, atrial, fibrillation, ventricular tachycardia, ventricular flutter, and ventricular fibrillation [8].

All pieces of contextual diagnosis come to a final one. Algorithm III: QRS features extraction in time domain [10]: \( \overline{F}_1 \) - polarity; \( \overline{F}_2 \) - relative height; \( \overline{F}_3 \) - relative width; \( \overline{F}_4 \) - relative mean square; and \( \overline{F}_5 \sim \overline{F}_7 \) - relative intervals. Parameter 1: the number of features, initialized by 7.

Algorithm IV: Singularity detection by means of WT:

\[
w^{j+1}(x_{j+1}) \cdot w^j(x_j) > 0 \quad \text{and} \quad \left| x_{j+1} - x_j \right| < \delta
\]

Parameter 1: Thresholds in each scale, initialized by \( \delta_{0-3} = \{0,5,0,4,0,3,0,5\} \).

4.2 SI Knowledge Source

If \( RR \) indicates the interval between two R-peaks, \( ARR \), refers the average R-R interval of eight update \( RR \) intervals, footnote \( i \) means the current beat and \( i-1 \) refers to the front one, then these Abenstein Criterion can be used as the rules to classify QRS complex in computer [11].

But Abenstein Criterion is just the most general criterion for QRS recognition, which is not enough for some special cases. Fuzzy ARTMAP network is used as the knowledge acquisition tool of the system.

R1: \( IF \ F_1 < -0.1 \) and \( -0.1 < F_2 < 0.1 \)

THEN PVC

R2: \( IF \ F_1 < -0.1 \) and \( -0.9 < F_3 < -0.1 \) and \( \alpha > 0 \)

THEN PVC

R3: \( IF \ F_2 < -0.1 \) and \( -1.1 < F_3 < -0.9 \) and \( \alpha > 0 \)

THEN inserted PVC

R4: \( IF \ F_3 < -0.67 \) and \( -0.1 < F_3 < 0.1 \)

THEN R on T

R5: \( IF \ RR_{i-1} > 0.9AR_{i-4} \) and \( RR_{i-1} < 0.9AR_{i-4} \)

and \( 1.9AR_{i-4} < RR_{i-3} + RR_{i-2} < 2.1AR_{i-4} \)

and \( 1.9AR_{i-2} < RR_{i-1} + RR_i < 2.1AR_{i-2} \)

THEN bigeminy

R6: \( IF \ RR_{i-2} < 0.9AR_{i-3} \) and \( RR_{i-1} < 0.9AR_{i-3} \)

and \( 1.9AR_{i-3} < RR_{i-3} + RR_{i-2} < 2.1AR_{i-3} \)

THEN trigeminy

R7: \( IF \ F_2 < -0.1 \) and \( F_1 < 0.9F_6 - 0.1 \)

THEN noise or couplet with the next PVC

R8: \( IF \ F_2 < -0.1 \) and \( \alpha < 0 \)

THEN noise

R9: \( IF \ -0.1 < F_7 < 0.1 \)

THEN N

Supplement R1 (which is extracted by Fuzzy ARTMAP[3-4]):
Fig. 2 A flowchart for the CAIS bi-directional interaction in a typical scenario
4.4 RP Knowledge Source

R1: IF A missing exists

THEN Reprocess the data in the missing range with thresholds on each scale decrease a half.

R2: IF thresholds have been halved and no R-peak is detected yet

THEN SI KS is triggered.

R3: IF the type of singularity is needed

THEN Algorithm II is activated

4.5 DFD Knowledge Source

R1: IF PVC and noise hypotheses exist both

THEN the type of singularity is needed

The interpretation process of No. 603 data block of record #200 in MIT/BIH Arrhythmia Database is shown as Fig. 2. All the data in the block is processed by Algorithm I firstly. The wavelet representation of the data is obtained. Then singularity detection method-Algorithm IV is applied with parameters initialized by \( \delta_{0,3} = (0.5,0.5,0.5,0.5) \), and point 29, 332, and 592 are detected as R-peaks separately. According to R2 in DCD KS, a missing conflict exists during point 604 to 904. Then the RP KS is triggered and the data in the missing range is reprocessed by Algorithm I with half thresholds \( \delta_{0,3} = (0.25,0.25,0.25,0.25) \). At this time, point 788 is detected as a R-peak. Then the process of R-peak detection is continued and point 926 is detected as R-peak also. Up to now, five R-peaks are detected in this data block altogether, and they are points 29, 332, 592, 788 and 926 respectively. Algorithm III is applied to extract shape features of those five QRS-complexes in the third scale of approximate signal, which respectively corresponding to point 4, 41, 74, 94, and 116 in that scale. Seven shape and interval features of each QRS-complex are obtained as \( F_i \sim F_7 \) in Fig. 2.

SI KS is triggered consequently. R7 and supplement R1 are both satisfied for point 94. According to R7, Point 94 is noise or composite couples with Point 116. While according to supplement R1, Point 94 is PVC.

At this time, DFD KS is triggered. According to R1 in DFD KS, the type of singularity is Lipschitz exponent of Point 94 is needed to compute. So Algorithm II in SP KS is activated and \( \alpha = 0.0125 \) is obtained. The features of point 94 ( \( F_i = -0.4413 \), \( F_5 = -0.8268 \), \( \alpha = 0.0125 \) ) are matched with SI KS R2's condition, which is \( IF F_i < -0.1 \) and \( -0.9 < F_5 < -0.1 \) and \( \alpha > 0 \), then Point 94 is PVC. To give the prediction to the next block is the last step of this block, which is that there is a R-peak near Point 21 in the next block. Then the interpretation of this block is ended and that of the next block is started.

5. Conclusions

Two feedback loops that are caused by bi-directional interaction can be observed in Fig. 2. The first feedback loop makes point 592, a PVC beat with rather low amplitude, not missed as usual methods do. This loop means that the solution in CAIS is not achieved monotonically, i.e. part of the hypothesis may be retracted as a consequence of tests that did not verify the expectations. Some signal can be re-analyzed by means of the same method with changed control parameters in response to the need of signal interpretation.

The second feedback loop makes the system to compute the type of singularity only for point 788, whose type of beat can not determined just by common features. This loop means that a selective focus of attention is adopted in the system. Rough estimates are done first, while precise computations are postponed to later stages until an interpretation to some extent has already existed.

The above two feedback loops i.e. bi-directional interactions make the system run in a kind of way that is rather close to human mode of thinking.

References


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