

Intelligent Cardiac Telemonitoring System

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Abstract

Our project tried to improve the repeatability and quality of vital parameter measurements performed at home. Our efforts focused on four issues (a-d)

(a) A new electrode reversal detection algorithm that can correctly decide whether electrodes were reversed in 94.87% of the cases and can determine the proper reversal order in 85.32% of the cases. (b) The influence of electrode misplacements (1 cm) was studied by comparing QRS, PQ, QT, R, T and ST60 parameters. We found significant differences between the correctly positioned and misplaced parameters which underlines the importance of correct placement. (c) A modified Minnesota Coding system was developed which was 9.3% more efficient when coding the 3-1, 3-2, 6-4-1, 7-1-1, 7-2-1, 7-3, 7-4 rules. (d) A lead estimation process is developed which estimates the unmeasured precordial leads from the measured I, II, V2 leads with 98.09% correlation in average.

1. Introduction

Cardiovascular diseases (CVD) are the leading causes of morbidity and mortality in most industrialized nations. A part of diagnostics and mainly the treatment of chronic phases of CVD could be managed cost-effectively by an intensive use of telemedicine. The early generations of cardiac telemonitoring set-ups used information technology mainly to transmit recorded signals, while signal evaluation remained exclusively the task of cardiologists in the monitoring center e.g.[1]. However, considering the spread of telemonitoring, the assistance of information technology (IT) is necessary in quality assurance of measurements, in data processing, data evaluation, data storage, retrieval, etc. To meet the requirements listed above, several projects were initiated all over the world e.g. [2]. The Intelligent Cardiac Telemonitoring System (ICTS) presented in this paper provides cost-effective and comfortable means of medical care as it supports examinations (ECG, blood pressure) to be performed conveniently at home, and the results to be transmitted to a central medical database for automatic evaluation. If necessary, an automatic alarm is generated and the actual signals and information preceding the alarm is sent to a 24-hour monitoring service for human evaluation. An alarm is an indicator of a significant

change in clinically meaningful signal parameters, but the final medical diagnosis is to be drawn by the cardiologist at the monitoring center.

We developed various methods to ensure the quality of home measurements and to improve the diagnostic efficiency. This paper presents (a) an ECG electrode reversal detection and correction algorithm, (b) an assessment of the electrode misplacements, (c) the modified Minnesota Coding system and (d) a lead estimation method for diagnostic efficiency improvement. These algorithms were integrated into the ICTS.

2. Methods

Electrode reversal detection and correction

To improve the quality of home measurements, a procedure was developed to detect and if possible, to correct electrode reversal mistakes.

The method is based on a systematic comparison of the correlation matrix of baseline and actual signals with a set of correlation matrices characterizing the correlation of baseline measurements with the leads of the possible electrode permutations.

The correlation between reversed (3-lead ECG) and normal (correctly placed) signal morphology is examined in 24 cases (1 correct electrode placement, and 23 variants of all the possible electrode placement errors). This procedure results in 24 (3 by 3) matrices, whose elements represent the correlation between the right original lead set i. e. the baseline measurement and the reversed one. Each of these matrices is characteristic to a specific lead reversal. An example is shown in Table 1., when RA and LA electrodes are reversed. The I_r , II_r , $V2_r$ represent reversed leads.

	I	II	V2
I_r	0.89	0.99	0.57
II_r	0.98	0.89	0.51
$V2_r$	0.51	0.57	0.98

Table 1. Correlation matrix when RA and LA electrodes are reversed.

If there is an incoming follow-up measurement in the ICTS, the algorithm systematically generates the 3 by 3

correlation matrix between the incoming recent measurement and the baseline measurement stored in the database. Each reversal case is represented with 9 matrix elements.

The algorithm first decides whether the electrodes were reversed or not and if they were then it tries to determine which was the reversal order and reconstructs the proper order.

The feasibility of the above principle was tested by (quadratic) discriminant analysis using a training sample of 150 ECG records (120 sec., 1000Hz, 12-lead) in each group of reversal. The testing sample included 65 ECGs in each reversal group i.e. the total dataset of the test comprised 1560 ECG measurements (60 sec., 600Hz, 3-lead) of 10 healthy male subjects (aged between 18 and 26) and a single baseline measurement (60 sec., 600Hz, 12-lead) for each subject. The 10 subjects were monitored for 6 months.

First the correct vs. non-correct placement classification was examined. Subsequently the classification efficiency was examined for each possible reversal group and the original group.

Electrode misplacement

The electrodes were systematically placed 1 cm up, down, right and left to the RA, LA and V2 electrodes. Only one electrode was misplaced once, while the others were kept in their correct locations. In this way 13 different groups were created. For the experimental evaluation 1040 ECG measurements (60 sec., 600 Hz, 3-lead) were taken. A total of 80 young men aged between 18 and 26 without clinical evidence of coronary heart disease were enrolled in the trial.

The differences between the R, T, ST60 amplitudes and the QRS, PQ, QT durations were examined. The normality of parameter distributions was examined by Kolmogorov-Smirnov tests completed at 0.001 significance level. To compare the parameters lead by lead in the 13 different groups, one-way ANOVA was used.

Modified Minnesota Coding system

The ICTS uses the Minnesota Coding system (MC) [3, 4] to evaluate the 12-lead baseline measurements (taken at the monitoring service at admittance).

Our signal processing method detects automatically the wave limits that can be adjusted by a special program. The P-onset, the P-offset, the QRS-onset, the QRS-offset and the T-offset points can be modified interactively by the program. This option is essential because the automatic detection algorithm sometimes fails.

A minor amplitude or duration change may result in a significant MC change because ECGs are continuous whereas MC items are categorical [5].

This problem is crucial when coding the excluding rules that can suppress other Minnesota codes. To reduce the false diagnoses of the MC, some of the excluding rules (3-1, 3-2, 6-4-1, 7-1-1, 7-2-1, 7-3, 7-4) were

modified using fuzzy logic. Ranges were created instead of well defined limits and the risk of accepting a rule was determined. The risk of accepting a rule can be low or high. If the risk is too high the algorithm does not accept the rule.

To test the modified Minnesota Coding system, an ECG dataset including 181 ECGs (120 sec., 1000Hz, 12-lead) was used. A total of 49 male (12 with definite coronary heart disease) and 47 female (7 with definite coronary heart disease) patients aged between 23 and 69 were enrolled .

First the ECGs coded with the 3-1, 3-2, 6-4-1, 7-1-1, 7-2-1, 7-3, 7-4 MC codes were selected. Subsequently the results of the original and modified MC system were compared. If there was a difference between the results, a technician coder and a senior supervisor examined the results.

Personalized evaluation

To make the evaluation system personalized, a new learning type evaluation algorithm was developed. The method calculates the personalized decision thresholds by a learning algorithm for each ECG parameter of the patient. If any of the ECG parameter of the incoming measurements exceeds the decision threshold, then a significant change in that ECG parameter is present. The calculation of the thresholds (2SD*) is shown in Eq. (1).

$$2SD^* = 2 * (K_g * SD_g + K_p * SD_p) \quad (1)$$

$$K_p = \frac{N}{100}, \text{ if } N \leq 100; K_p = 1, \text{ if } N > 100 \quad (2)$$

$$K_g = 1 - \frac{N}{100}, \text{ if } K_p \leq 100; K_g = 0, \text{ if } K_p > 100, \quad (3)$$

where SD_p is the standard deviation of the home measurements, SD_g is the global standard deviation, K_p is the weight coefficient of SD_p , K_g is the weight coefficient of SD_g . The global parameters refer to the whole population and are categorized by age, sex and bodyweight [6].

From these thresholds the ranges are calculated for each ECG parameter by adding 2SD* values to the parameters of the baseline measurements and by subtracting 2SD* values from the parameters of the reference measurements. If the ECG parameter is normally distributed, then this range includes 95% of the normal parameters (if the distribution of the parameter is asymmetric, the thresholds can be calculated by the Chebisev inequality). After 100 follow-up measurements the threshold calculation is based exclusively on the patients' own measurements. This algorithm considers both day-to-day ECG variability and the electrode positioning errors. The thresholds obtained are used to detect significant changes compared to the baseline status.

This learning and evaluation method can also be used for blood pressure measurements as well in a similar way.

Lead estimation

The 3-lead ECG of the follow-up measurements has less diagnostic information than the 12-lead one [8]. To improve the diagnostic efficiency an estimation process was developed. The process estimates the precordial (V1,V3-V6) leads from the measured I, II, V2 leads. At first the baseline measurement is decomposed into a measured and a part to be estimated (Eq. (4)). Then the covariance matrix is calculated. The minor matrices of the 12x12 covariance matrix represent the relationship between the measured and the estimated part.

The precordial leads can be calculated for the 3-lead follow-up measurement, from the parameter matrix E . The personalized matrix E can be calculated from the covariance matrix K (Eq. (5)). A personalized parameter matrix belongs to each baseline measurement. It was shown elsewhere that the method outlined provides optimal estimates in least square sense [7].

$$\bar{\varphi}_c = \begin{bmatrix} \bar{\varphi}_m \\ \bar{\varphi}_{est} \end{bmatrix} = \begin{bmatrix} \varphi_{m1} \\ \vdots \\ \varphi_{mn} \\ \varphi_{est1} \\ \vdots \\ \varphi_{estm} \end{bmatrix}, \quad (4)$$

where $\varphi_{m1} \dots \varphi_{mn}$ are the measured leads, $\varphi_{est1} \dots \varphi_{estm}$ are the estimated leads, n is the number of the measured leads m is the number of the estimated leads and $m+n=p$.

$$\bar{\varphi}_{est} = \bar{E} \cdot \bar{\varphi}_m; \bar{E} = \bar{K}'_{12} \cdot \bar{K}_{11}^{-1}; \bar{K} = \begin{bmatrix} k_{11} & \dots & k_{1p} \\ \vdots & \ddots & \vdots \\ k_{p1} & \dots & k_{pp} \end{bmatrix} \quad (5)$$

The algorithm was also tested using a global K matrix, which is a general (not personalized) matrix and can be used for anyone.

3. Results

Electrode reversal detection and correction

The first quadratic discriminant analysis revealed that in 94.87% of the cases the electrode reversal algorithm can correctly decide whether the electrodes were reversed or not. The second analysis revealed that the algorithm can correctly determine which was the reversal order in 85.32% of the cases. In 12 groups the decision efficiency was at least 90%, in 6 groups the efficiency was between 80% and 90% and in 6 groups the efficiency was lower than 80%. The second analysis also showed that there were 11 groups which were the most likely targets of classification errors.

Electrode misplacement

Kolmogorov-Smirnov test showed that ECG parameters (R, T, ST60, QRS, QT, PQ) in all the 13 groups were normally distributed with a significance of < 0.001. The R amplitude, QRS, QT and PQ duration did not show significant difference in I, II, V2 leads. The T amplitude showed significant difference (with a

significance of < 0.001) in lead I between the first (correct) group and the 8th (LA electrode down 1 cm) group and in the V2 lead between the first (correct) group and the 10th (V2 electrode up 1 cm) group. ST60 amplitude showed significant difference (with a significance of < 0.001) in lead I between the first (correct) and the 8th (LA electrode down 1 cm) and in the V2 lead between the first (correct) and the 10th (V2 electrode up 1 cm) and 11th (V2 electrode right 1 cm) and 12th (V2 electrode down 1 cm), groups respectively.

Modified Minnesota Coding system

Out of the 181 ECGs 28 ones were coded with excluding rules that were modified with fuzzy logic. In 6 of the cases the modified MC system did not accept some excluding rules and in these cases other non excluding rules were coded (in agreement with the two human coders). For example there was a man aged 45 who had 120ms QRS duration so the 7-4 Minnesota rule was coded and all 2-, 3-, 4- and 5-codes, 9-2, 9-4, 9-5 were excluded. The fuzzy based MC system determined that the risk of accepting the 7-4 rule is high so the rules above were considered and 4-1 MC was coded which agreed with the two human coders. In 11 of the cases the modified MC system did not accept some excluding rules and other non excluding rules were not coded (in agreement with the two human coders).

Personalized evaluation

The testing of the personalized evaluation algorithm is in progress. Preliminary results will be available soon.

Lead estimation

To determine the efficiency of the estimation algorithm of the ICTS, the correlation between the original 12-lead ECG and the estimated 12-lead ECG was examined. For the statistical evaluation the ECG dataset of the modified MC system was used. In our procedure the "measured" I, II, V2 leads were selected from the 12-lead ECG records and subsequently the remaining "unmeasured" leads were calculated. Finally the original and the estimated leads were correlated lead by lead. If a global parameter matrix was used, the correlations between the original and estimated V1, V3, V4, V5, V6 leads were 82.36%, 78.83%, 81.82%, 83.25% and 91.29% respectively (average correlation 83.51%). Using personalized parameter matrices the correlations between the original and estimated V1, V3, V4, V5, V6 leads were 96.35%, 97.78%, 98.21%, 98.94% and 99.18% respectively (average correlation 98.09%).

4. Discussion and conclusions

Most of the previously reported methods can only detect the erroneous electrode placement of a single lead, e.g. lead I [9]. Our electrode reversal detection and correction method can detect electrode placement errors in all the I, II, V2 leads. The decision boundaries elaborated handle properly the electrode reversal detection even in the presence of time dependent

variability of ECG parameters. The two-class problem of electrode reversal was correctly classified in 94.87% of the cases. The precise reversal order classification (24-class problem) was correct in 85.32% of the cases. The probability of mis-classification can be reduced by marking those groups which are the most likely targets of classifications errors. For example, if group 14 classified as group 20 sixteen times then we mark group 20. In our system if the classification chooses a marked group, we only return a reversal error message to the patient but do not try to correct it. Despite the promising results, we should keep in mind, that the test set available was rather small compared to the dimensionality of the decision problem.

The electrode location error is an important source of ECG parameter variability. In our study the influence of placing electrodes (RA, LA, V2) 1 cm from their correct locations was examined. Out of all the possible misplacements 13 options were examined. Only one electrode was misplaced once, while the others were kept in their correct places. In T and ST60 amplitudes significant differences were found between the correctly placed and misplaced electrode groups. These parameters can affect the final diagnosis so the proper placement is essential. R amplitude, QRS, QT and PQ duration did not show significant difference. Probably the 1 cm misplacement did not affect these parameters. Another reported work found similar results [10].

The evaluation of the baseline ECG was based on the modified Minnesota coding system. The 3-1, 3-2, 6-4-1, 7-1-1, 7-2-1, 7-3, 7-4 excluding rules were modified using fuzzy logic. We had 17 cases when the modified MC system did not accept some of these rules. In 6 cases without these rules other non excluding rules were coded and in 11 cases non excluding rules were not coded. This comparison showed that the efficiency of the original MC [3, 4] can be improved. Other rules of the MC can be also modified using the fuzzy logic, but it has to be noted that the complexity will increase substantially with the number of the conditions of a rule.

A personalized learning type evaluation method was also presented. The results of this algorithm are not yet available, but according to our expectation this algorithm will be more sensitive than others which use global decision thresholds.

The performance of a lead estimation process was examined using personal and global estimate matrices. A 3-lead ECG was selected from the 12-lead one, and leads disregarded were estimated and finally the original 12-lead one was compared with the estimated one. Results showed 83.51% (global matrix) and 98.09% (personal matrix) correlation between the original and the estimated lead set. This result yielded the minimal error of

estimation procedure, because no other sources of variability (temporal and, misplacement errors) were considered.

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