Electrode reversal detection in ECG remote monitoring

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Abstract. *Most state-of-the-art cardiac telemonitoring systems lack the automated process of analyzing recorded data for electrode reversal. Although some methods exist to cover a very limited number of possible reversal cases like the detection of lead I reversal, these methods are totally unaware of any personalized a priori information on the ECG signals of the person monitorized and rely solely on lead signal parameters and properties – GRI and Marquette criteria inspection or training ANNs [1]. This paper will describe the concepts of the method developed to detect and recover incorrectly recorded ECG signals using previously recorded data. Some details on system operation and architecture will be also included. Results include probability of over 90% of detecting lead reversal.*

Keywords: ECG recording, electrode misplacement/reversal detection, signal recovery

1. Introduction

The workflow of the remote monitoring process is shown in figure 1. For each patient, baseline measurements and medical diagnosis are made by the monitoring service; correspondent risk factors are also recorded [2,3,4]. Baseline measurements are used for the basis of comparison with the follow-up measurements.

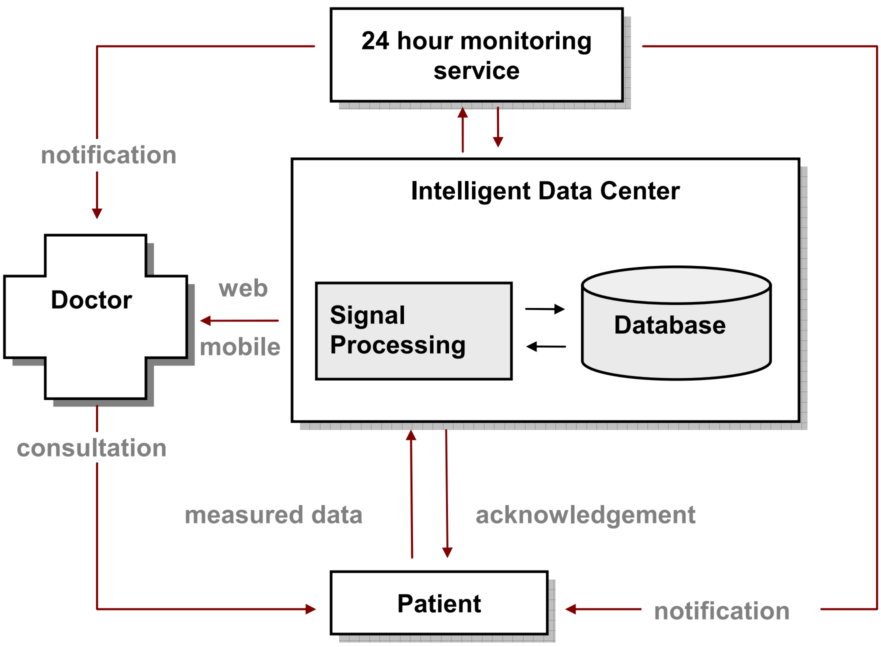

Fig. 1. The workflow of the remote monitoring process.

Home measurements are done via the patient care unit connected with a Bluetooth capable mobile phone or computer. Each measurement is transferred to the Intelligent Data Center where the collected data is automatically evaluated. The time interval between measurements is predefined; however the patient can fire measurements at any time, for example in the case of chest pain. The time interval between measurements can be changed remotely from the Data Center. There is a need for additional signal processing on the recorded ECG before evaluation to correct smaller errors of misplacement or to filter and to generate an average period of the quasi-periodic signal. In case of an alert, the evaluated ECG is transmitted to the cardiologist at the monitoring service, who can take immediate actions, if necessary. The incoming measurements are acknowledged by the monitoring center in form of SMS or e-mail transferred to the patient. All measured data is stored in the database and General Practitioners can access all their patients' Electric Patient Record (EPR).

2. Subject and Methods

The most common mistake regarding to home measurements is the misplacement of the color-coded electrodes. Our method deals with the problem, when the electrodes are placed accurately on the body, but the order of the colors referring to body positions are interchanged. The diagnostic procedure of the system will fail if the electrodes are placed in wrong order. Because of the electrode reversal, the recorded signal can either show a large bias or suggest malignant acute pathological condition from smaller but significant waveform alterations.

A three lead ECG patient unit with four electrodes is used for home measurements. The four electrodes have different colors to facilitate correct electrode placements in definite positions on the body. Those are the left shoulder, right shoulder, left leg and the V2 lead point on the chest. There are 24 different permutation of assigning the four color-coded electrodes to the four points of the body. Our aim was to develop an algorithm, which is capable of efficiently recognizing electrode reversal while not being computationally expensive on the server-side.

We have tested how the shape of the signals recorded in the 23 wrong positions correlate to the correct ones.

	Lead I	Lead II	Lead V2
Reversed Lead I	0.89	1.00	0.57
Reversed Lead II	1.00	0.89	0.51
Reversed Lead V2	0.51	0.57	1.00

Fig.2.: Correlation matrix in case of electrode reversal on the left leg and right hand

The investigation involved the generation of the 24 possible signals from 150 previous measurements and the calculation of the correspondent correlation matrixes. In most of the reversals, the correlation matrixes show significant similarities, thus revealing the reversal itself.

A sample correlation matrix (see Fig.2.) shows the error caused by mixing the positions of the electrodes for the right hand and left leg. We defined the 24 correlation matrixes according to our test measurements. Whenever a new measurement is taken, a correlation matrix is calculated referring to the similarities of the measured and the baseline data. The calculated matrix is compared to the 24 pre-defined matrixes and the measurement is classified, by statistical methods.

The correct I, II, V2 values can be calculated from the measured I_r, II_r, $V2_r$, using equation (1), where M_i is the electrode reversal matrix. The M_i matrix is calculated for all reversal cases using matrix-inversion methods.

$$\begin{bmatrix} I \\ II \\ V2 \end{bmatrix} = M_i \times \begin{bmatrix} I_r \\ II_r \\ V2_r \end{bmatrix} \qquad (1)$$

Whenever an electrode reversal is made, if it can be classified with confidence, then the recorded signals can be corrected. In case of uncertainty about the classification, the patient can be ordered to check the placement of the electrodes and repeat the measurement. The automatic conversation is done by the endorsement of the cardiologist at the measurement center.

Classification methods were used to set up different group centroids for the different reversal groups, then to identify the measured reversal case. Different methods were tested to set up classification groups – linear, quadratic, Mahalanobis – resulting in different efficiencies of recognition. Separated training and sample groups were also used to cross-validate the methods. The total dataset used includes 1500 ECG measurements (60 sec., 600Hz, 3-lead) of 10 healthy male subjects (aged between 18 and 26) with a single baseline measurement (60 sec., 1000Hz, 12-lead) for each subject. The 10 subjects were monitored for 6 months.

3. Results

A relatively small amount of recordings were available to train and test the methods – 1500 samples for all the 24 reversal groups – this means an average of 60 in every group. As the number of samples assigned to a particular group is very low considering the number of groups this implies that the classification methods could not have yet been expected to provide an acceptable error rate for cross-validation. Further acquisition of data is expected to improve reversal recognition and to lower misrecognition error.

The three different classification functions used were linear, quadratic and Mahalanobis. The scenarios included determining correct/incorrect placement of electrodes, the identification of reversal setup, both by using the same training and sample set and by using 80% of the samples to train and 20% to test the classification functions.

Our test included multiple runs of 3 different setups: classifications using linear, quadratic and Mahalanobis functions. The averaged results for detection of correct – incorrect placement yielded the following (see Fig 3.):

With cross-validation 80% training – 20% test	**Linear**	**Quadratic**	**Mahalanobis**
Specificity	75,25%	83,95%	86,62%
Sensitivity	100,00%	80,00%	50,00%
No cross-validation	**Linear**	**Quadratic**	**Mahalanobis**
Specificity	83,55%	90,64%	94,52%
Sensitivity	95,08%	98,41%	17,14%

Fig.3.: Specificity and sensitivity of classification using different test setups, functions

First results show a promisingly high rate of detection of correct vs. reversed placement of electrodes. With the measurements divided into these two groups using 80% of the samples to train the classification function and 20% to cross-validate it, the classification space could be effectively separated by the linear classification function.

The following results (see Fig.4.) show the number of recognized reversal groups at specified efficiencies using the full reversal set (24 cases). The classification function had to predict which group the actual reversal was of. As expected, the linear classification function could not fulfill this task, quadratic and Mahalanobis based functions performed almost identically effective.

With cross-validation 80% training – 20% test	Linear	Quadratic	Mahalanobis
Over 80% efficiency	2	10	9
Over 90% efficiency	1	7	4
No cross-validation	**Linear**	**Quadratic**	**Mahalanobis**
Over 80% efficiency	0	17	14
Over 90% efficiency	0	8	7

Fig.4.: Number of groups detected at different efficiency rates (24 reversal groups total)

4. Discussion

These early stage measurements and classification tests already show a high and promising rate of lead reversal detection, an artificial intelligence method of the referred remote monitoring system to improve measurement reliability and efficiency. The introduced method is independent of the underlying architecture, but using this particular setup it would make it possible to reliably detect lead reversal with over 95% probability and advise the patient with instructions to take at over 80% probability in almost 50% of the reversal cases.

The introduced tests used measurements from different reliability (reversal measurements performed by non-professionals) what implies that this method could further improve with acquisition of proper signal samples. The relatively low efficiency values could be accounted to the fact that the 1500 measurements originate from different patients and different points in time what implies the error of electrode misplacement is significant. The results will also most probably show improvement by the reduction of classification variables what will be one of the future tasks.

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References

[1] Bo Hedén MD, Mattias Ohlsson MSc, Lars Edenbrandt MD PhD, Ralf Rittner MSc, Olle Pahlm MD PhD, Carsten Peterson PhD: Artificial Neural Networks for Recognition of Electrocardiographic Lead Reversal. Am. J Cardiol 1995;75:929-933

[2] B Végső, G Balázs, Gy Kozmann: Properties of an Intelligent Cardiac Telemonitoring System. IME, 2004, III/8:47-52

[3] G. Balázs, I. Vassányi, B. Drozdik, E. Mógor: Medical Information Systems for Cardiac Risk Assessment and Remote Monitoring. Proceedings of Medical Informatics Europe 2002: 635-638. IOS Press, 2002

[4] G Balázs, Gy Kozmann, I Vassányi: Intelligent Cardiac Telemonitoring System. Computers in Cardiology, IEEE, 2004:745-748