New VCG and ECG indexes for early identification of Acute Myocardial Infarction patients

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Abstract— **A novel electrocardiographic (ECG) and vectorcardiographic (VCG) signal processing technique is proposed for identification of patients with Acute Myocardial Infarction (AMI). To this end, we propose a method based on two QRS-loops features: a) Volume, and b) Planar Area; along with five orthogonal ECG indexes: c) ST-T vector difference, d) T vector difference, and e-g) the area under the T-wave in X, Y and Z leads. Our method was tested using ECG recordings of 97 AMIs and 52 healthy subject from the PhysioNet PTB database. The results indicate that these indexes show significant statistical differences (p-values <0.05) between the two populations (Healthy versus AMI population, with the exception of c). To validate the suggested index a 70/30 cross validation technique was used. Moreover, combining all parameters (with the exception of the T-wave area in Y and Z leads), it was possible to classify the AMI and healthy subjects with a sensitivity = 93.90%, a specificity = 93.44% and an accuracy = 93.73%, applying a linear discriminant classifier method. We conclude that the proposed technique could be used as an alternative diagnostic technique in the emergency room.**

Keywords— **ECG, VCG, AMI.**

I. INTRODUCTION

The Acute Myocardial Infarction (AMI) is a portion of cardiac tissue necrosis that usually happens when the coronary vessels have been completely or partially blocked. When cardiac ischemia (CI) persists in time leads to myocardial necrosis (infarction) and produces an electromechanical dissociation, which could generate arrhythmias, ventricular fibrillation and sudden death. Thus, the AMI is the main cause of death worldwide [1]

In addition, CI causes changes in the energy dependent (ATP) pumps located within the cardiac cells sarcolemma, which modify the transmembrane potential, usually recorded as changes in the electrocardiogram (ECG) and vectorcardiogram (VCG). During ventricular repolarization these changes include ST segment displacement, dispersion of ventricular repolarization and T-wave alternans. Similarly, it has been also shown that these ECG and VCG modifications are recorded signals during depolarization, such as the QT-interval and the Q-wave shape and size [1,2].

Based on the new technologies and advances in digital ECG analysis, several techniques have been developed that use the VCG constructed from ECG for monitoring patients with CI [3,4] and after an AMI episode [5,6]. In the same way, several investigators have also used ECG and VCG techniques for AMI detection [7–9].

In this paper, we develop a new technique for processing ECG and VCG signals in order to identify patients with AMI and to differentiate them from healthy subjects. The hypothesis of this study is to determine early and as accurately as possible when a patient has suffered an AMI. The great advantages of the proposed ECG and VCG technique are: very low cost; non-invasive and it can be carried out repeatedly without causing any harm to the patient.

II. MATERIALS

We used ECG records from 97 patients with AMI (71 men, age 58 ± 10 yrs, and 26 women, age 64 ± 12 yrs) that were obtained during the week after the AMI episode. ECG's from 52 healthy subjects (39 men, age 42 ± 14 yrs, and 13 women, age 48 ± 19yrs) were the control group. All data were obtained from the *Physikalisch-Technische Bundesanstalt* (PTB) data base of the National Metrology Institute of Germany, available at *Physionet*. Each record includes 15 simultaneously measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1-V6) together with the 3-Frank lead-ECGs (X, Y, Z). Each signal was digitized at 1000 Hz, with 16 bits of amplitude resolution[10]. It is underlined that only the orthogonal ECG leads (X, Y, Z) were used to derive the VCG [11].

The areas of myocardial necrosis shown by the ECG's of the AMI group were: anterior (n=14), antero-lateral (n=10), antero-septal (n=24), antero-septo-lateral (n=1), inferior (n=23), infero-lateral (n=17), infero-postero-lateral (n=6), lateral (n=1), posterior (n=1).

III. METHODS

All ECG records (X, Y, Z) were pre-processed as follows: a) A band-pass filter (Butterworth, 4th order, 0.2-100 Hz, bidirectional) to reduce low and high frequency noise and a notch filter (Butterworth, 2th order, 50/60 Hz, bidirectional) to minimize the power line interference were applied. b) A cubic spline interpolation filter was used to attenuate ECG baseline drifts and respiratory artifacts. c) When all records were filtered, the QRS-complex, T-waves and their endpoints were detected for each ECG using by means of a wavelet-based technique [11]. d) Excessive noisy beats (with a RMS noise level >40µV, measured within a 40 ms window located at 2/3 of the RR interval) were excluded. e) In addition, ectopic beats were also eliminated by comparing incoming signals against a previously established template with the use of a cross-correlation technique. Besides, a visually low noise sinus beat extracted from the ECG record was selected as template (or reference).

After such ECG signal adaptation (or pre-processing), we carried out the feature extraction step. Figure 1 shows a general block diagram of the procedure.

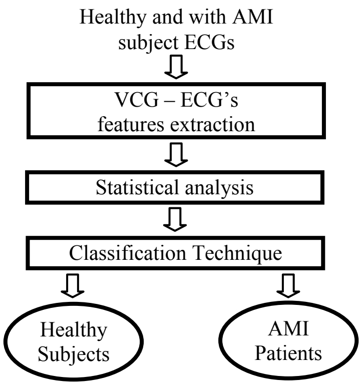

Figure 1-General block diagram of the proposed technique

A. Parameter Calculation

Two parameters of the QRS-loop (VCG), representing ventricular depolarization, and five from orthogonal ECG leads (X, Y, Z), representing ventricular repolarization, were computed in this step. Some of these parameters have already been proposed by this group to study the dynamic ECG and VCG changes during an episode of CI [3,4,11].

- *QRS-loop Volume* (***QRS***$_V$) [mV^3]: It is the group of points that generates the Minimal Convex Volume (MCV) enclosing all points of the QRS-loop. It aims at quantifying the loop flatness and morphology in 3D [11].
- *QRS-loop Planar Area* (***QRS***$_{PA}$) [mV^2]: It estimates the inner loop area, obtained by projecting the QRS-loop on the best adjusted plane computed by least mean squares (Optimum Plane). It reflects hemodynamic-related cardiac pathologies [11] (Figure 2-a).
- *ST-T Vector Difference* (***ST-T***$_{VD}$) [mVs]: It is defined as the difference in area between the ST-T interval (from the J-point to the T-wave end) and the ECG reference (at ST-T) evaluated at the first 30 s of each record (Figure 2-b). Its objective is to estimate all changes produced during left ventricular repolarization [4].
- *T-wave Vector Difference* (***T***$_{VD}$) [mVs]: It is defined as the difference area between the ECG signal at the current T-wave interval and the reference (T-wave interval), evaluated during the first 30s of each record [4] (Figure 2-c). This parameter estimates changes produced during middle and end ventricular repolarization.
- *Area under T-wave in X, Y and Z leds* (***aT***$_X$, ***aT***$_Y$, ***aT***$_Z$) [mVs]: It is defined as the difference area between the ECG signal at the current T-wave and the abscissa. It estimates repolarization energy (Fig. 2-d).

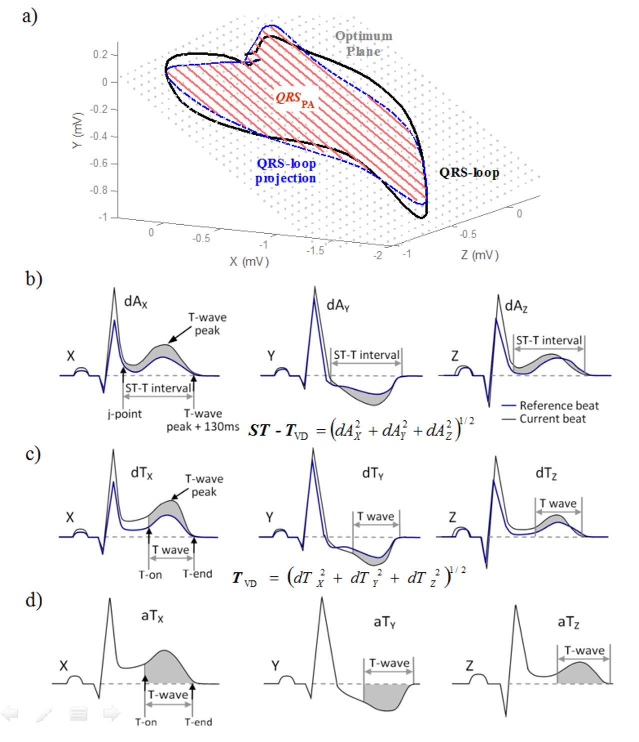

Figure 2-Parameter Calculation

B. Statistically Analysis

The described indexes were computed for each detected sinus beat in each ECG record. Comparisons between mean values were computed for both populations using the non-parametric Mann-Whitney test.

C. Classification technique

After the descriptive analysis, linear discriminant analysis (LDA) [13] was applied to the parameters obtained for each patient. In other words, the intent was to predict whether the ECG's belonged to the healthy group or to the AMI group.

The discriminant function (fd) obtained from the LDA can be used to classify each ECG record as belonging to a particular group (Healthy or AMI). The LDA technique estimates the coefficients of the fd from a subset of ECG records whose group is known. This subset of observations is sometimes referred to as the training subset (we used 70% of the records). To validate the model, this discriminant function was used to predict the group of another different subset (referred to as validation subset), making use of the remaining 30% of the records.

IV. RESULTS

Descriptive analysis results are shown in Table 1, where mean values (M) and standard deviations (SD) are displayed. They were computed for each ECG record of Healthy and AMI Subjects. The significance p-values of the statistical comparison between both populations are also included. In patients with more than one ECG record during the first week after the AMI episode, we averaged out the parameter values, so that each corresponded to a single value for each index.

Table 1 Mean values (M) and standard deviations (SD) of each parameter for both populations and statistical significance (p-value)

Subject		QRS_V [mV^3]	QRS_{PA} [mV^2]	$ST\text{-}T_{VD}$ [mVs]	T_{VD} [mVs]	aT_X [mVs]	aT_Y [mVs]	aT_Z [mVs]
Healthy	M	0,15	1,22	4,43	4,36	40,25	21,93	-22,11
	SD	0,16	0,65	1,49	3,18	20,69	11,92	17,96
AMI	M	0,06	0,55	5,11	15,38	9,56	10,51	-8,06
	SD	0,04	0,29	2,57	23,66	16,57	18,15	24,46
p-value		<0,01	<0,01	,091	<0,01	<0,01	<0,01	<0,01

To evaluate the classification performance, we determined 3 statistical indexes to compare the results predicted by the proposed algorithm against the classification given by the database. These indexes were sensitivity (Sen), specificity (Spe) and accuracy (Acc). Table 2 shows the results of the LDA classification using each parameter and the best combination of them (BC). The BC of parameters was determined using the Lambda Wilks minimization technique, which determines the smallest set of discriminant variables that contributes most to the group differentiation [13,14]. Hence, it was found that the BC was QRS_V, QRS_{PA}, $ST\text{-}T_{VD}$, T_{VD} and aT_X.

Table 2 Classification outcomes for each computed index and for the BC

	QRS_V	QRS_{PA}	$ST\text{-}T_{VD}$	T_{VD}	aT_X	aT_Y	aT_Z	***BC***
Sen (%)	69,79	90,76	56,69	71,34	79,45	65,62	73,93	**93.90**
Spe (%)	76,81	73,69	61,94	79,63	84,00	72,50	54,00	**93.44**
Acc (%)	72,29	84,69	58,56	74,29	81,07	68,07	66,84	**93.73**

V. DISCUSSION Y CONCLUSION

In recent years, several researchers have proposed different techniques using the same data base (PTB) to identifying patients with AMI, based on the surface ECG. Among which we can mention: Bakul *et al.*[7], who have developed a set of features called *Relative Frequency Band Coefficient* to automatic identification of AMI risk, reaching a Sen = 85.57%, Spe = 83.97% and Acc = 85.23%. Moreover, Keshtkar *et al.* [8] have proposed the evaluation of the *wavelet coefficients set* computed on the *average ECG signal* through neural networks as indexes to detect the AMI achieving a Sen = 93%, Spe = 86% and Acc = 89.5%. Meanwhile, Maharaj and Alonso [9], using a multivariate discriminant classifier based on *multiscale wavelet ECG signal decomposition*, reached a Sen between 80 to 90% and a Spe = 90%. Although all these techniques have their advantages and disadvantages, no one makes reference to patients, age, gender, days since suffering AMI, and other clinical data. Also not report how many, or wish records of each patient were used. Besides, no information is given regarding the number of used records.

This work proposes a new technique for the early identification of patients with AMI. With this aim we only used the ECG's obtained during the week after AMI for each patient and proposed seven indexes, two measured from VCG and QRS_V QRS_{AP} and five computed on the X, Y, Z leads of de ECG signal $ST\text{-}T_{VD}$, T_{VD} y aT_X , aT_Y y aT_Z (see Table I). It can be seen that M's have a large dispersion because their SD's are often close to the M values. However, the statistical comparison produced significant differences (p-value <0.01) in all indexes (except $ST\text{-}T_{VD}$), suggesting that they may be used to correctly differentiate between these populations. Although the $\boldsymbol{ST\text{-}T}_{\mathrm{VD}}$ does not present significant differences between groups, it actually improves classification results when it is used along with the other selected parameters. Apparently, there are some borderline cases that are correctly classified when this feature is included.

From Table II, it can be see that the parameters with greater individual discriminating power are $\boldsymbol{QRS}_{\mathrm{PA}}$ and $\boldsymbol{aT}_{\mathrm{X}}$, also when combined with $\boldsymbol{QRS}_{\mathrm{V}}$, $\boldsymbol{ST\text{-}T}_{\mathrm{VD}}$ and $\boldsymbol{T}_{\mathrm{VD}}$, with a **Sen = 93.90%, Spe = 93.44%** and **Acc=93.73%.** This demonstrates the excellent performance of the proposed classification technique as compared with other researchers' results [7–9].

We conclude that the new multivariable AMI patient identification technique based on ECG and VCG indexes achieved excellent performance in differentiation populations with AMI and healthy subjects. It could be used as an alternative diagnostic technique in the emergency room.

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