# ECG-based Detection of Left Ventricle Hypertrophy

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Abstract:     This works proposes an electrocardiogram based approach for left ventricle hypertrophy (LVH) classification. LVH classification is based on features extracted from the ECG signal, where the main features are the ones related to the QRS wave amplitude and duration. Instead of working on only one LVH criteria, we employed a score which explores the complementarity of the best criteria through a fusion strategy. The best criteria are the ones which discriminate normal and LVH ECGs according to the t-test. We carried out experiments in a database with a group of fifty men, where a half has LVH. The gold standard to detect LVH was the left ventricle mass index measured using echocardiography. Our approach achieved a sensitivity of 69.7%, outperforming all LVH criteria.

## 1 INTRODUCTION

Left Ventricle Hypertrophy (LVH) is an important risk factor for cardiovascular morbidity and mortality, including sudden death (Kreger et al., 1987; Haider et al., 1998). The causes of LVH include obesity, increased blood viscosity, volume and pressure overload, and also non-pathological conditions, like in the case of some athletes where LVH is a normal adaptation of the myocardium. In chronic hypertension, which is characterized by changes in pressure and blood volume, structural changes in the myocardium usually occurs, leading to an increase in the mass of the left ventricle (LV) (Ganau et al. 1992). This mass increase can be detected and quantified by the echocardiogram, which is the gold standard for LVH. On the other hand, the electrocardiogram (ECG) can also be employed in LVH detection, although the diagnosis is qualitative, suggesting the presence or absence of LVH. In spite of that, the ECG is an exam widely employed to assess the condition of the heart, taking advantage of being easy to perform, noninvasive and cheap. These advantages make the ECG analysis an important step in the diagnosis of LVH.

Many criteria have been used to diagnose LVH through ECG, most of them employing the amplitude and duration of the QRS complex (Hancock et al., 2009; Mazzaro et al., 2008), since this wave reflects ventricular depolarization.

However, there is no agreement among experts about which criterion is more reliable and should, therefore, be used.

In this context, this work investigates the correlation between the electrocardiographic measurements and LVH. Furthermore, in order to explore the complementarity of the criteria proposed so far (Hancock et al., 2009; Mazzaro et al., 2008), this work proposes an original score based on the combination of the results of the best criteria. In our experiments, the criteria are implemented and tested in the same database composed of normal and LVH ECGs. The results are then compared against the echocardiogram report of the same individuals in the database.

## 2 MATERIALS AND METHODS

### 2.1 Left Ventricle Hypertrophy

LVH is defined as the thickening of the walls of the left ventricle, the main chamber of the heart. The gold standard for LVH detection is the echocardiogram, which uses ultrasound waves to measure the thickness of the ventricle. The left ventricle mass is then calculated by approximating the geometry and density of this chamber. However, the mass of the ventricle varies with the height of the

patient. This way, the left ventricle mass could indicate LVH for a 1.60 m tall patient, but not for a 1.90 m one. As a consequence, the left ventricle mass is indexed (LVMI) by height, or

$$LVMI = \frac{LVM}{h^{2.7}}, \qquad (1)$$

where $LVM$ is the left ventricle mass in grams and $h$ is the height of the patient in meters.

The ECG is another exam employed for LVH diagnosis. Besides being insensitive in detecting anatomic LVH and limited to obtain a quantitative measure of left ventricle mass, the ECG is used to infer qualitatively if the left ventricle is hypertrophied. A plenty of methods are used by the physicians to detect LVH through the ECG. Most of them uses the amplitude and the width of the QRS complex (Hancock et al., 2009). However, there is no agreement among the experts about which method is the most reliable. The methods used by the physicians can not keep specificity (rate of normal patients correctly classified) and sensibility (rate of LVH patients correctly classified) high at the same time. Indeed, to classify most of the LVH patients correctly some normal patients will also be classified as LVH, and vice-versa.

In order to find out which is the best method to detect LVH through the ECG, several methods yet proposed in the literature are tested, including additional characteristics extracted from the ECG, as follows:

- The peak amplitude of the QRS and T waves in all 12 leads.
- The duration of several intervals in the ECG in all 12 leads.
- The area of the QRS complex and of some intervals in the ECG.
- The angle of the electric axis of the heart.
- The presence of the strain pattern (Roman et al., 1987).

The main methods tested in this work are described in (Hancock et al., 2009) and the ones that achieved the best results are explained later in the table of results.

## 2.2 ECG Processing

In order to build a fully automatic method to detect LVH, the following steps are required:
- ECG segmentation,
- ECG feature extraction,
- LVH patient classification.

The first step is based on an automatic segmentation algorithm of the 12 lead ECG. In this

work, the segmentation provides the following ECG features:

- The beginning, peak and end of the QRS complex,
- The peak and end of the T wave.

The main feature is the peak of the QRS complex. From the peak position in time, all the other features are obtained. Our QRS peak detection algorithm is based on (Hamilton, 2002). From the QRS peak, a search for the onset and offset of the QRS complex is performed backward in order to find the plateau of the PQ interval, and forward until finding a decrease in the slope just after the J point. For the detection of the T wave peak, we have employed an algorithm based on the Mexican Hat Wavelet Transform. Among de ECG features, the most difficult to detect precisely is the end of the T wave (T wave offset). Even experienced experts differ from each other when determining the end of the T wave. Several algorithms have been proposed so far to detect the end of such wave (Martínez, 2004; Zhou, 2009; Zhou 2011). We have chosen a simple and accurate algorithm developed in (Zhang, 2006), which is based on the area under the T wave.

From the ECG segmentation, some features related to amplitudes and intervals are extracted from all 12-ECG leads. The whole set of features include patient data like blood pressure and body mass. It is important to emphasize that we have included features from the R, S and T wave amplitude and duration, the area under the QRS complex, the QT interval and the interval between the Q wave and the T wave peaks, the electrical axis and the strain pattern, besides the features already used so far by the cardiologists (Hancock et al., 2009).

The extracted ECG features are then combined according to each LVH criteria. Some selected criteria are summarized below:

- $(R + S)_{in\ any\ precordial\ lead}$ (Grant, 1957): the greatest sum of the $R$ and $S$ wave amplitudes $(R + S)$ among the precordial leads.
- $(R_I + S_{III})$ (Gubner and Ungerleider, 1943): the sum of the $R$ wave amplitude in lead $I$ and the S wave amplitude in lead $III$.
- $(largest\ R\ or\ S)_{in\ any\ precordial\ lead} \times t_{QRS}$ (Mazzaro et al., 2008): the highest $R$ or $S$ peaks among the precordial leads multiplied by the duration of the $QRS$ complex in that lead.

- $R_I$ (Gubner and Ungerleider, 1943): $R$ wave amplitude in lead $I$.
- $(R_I - S_I) + (S_{III} - R_{III})$ (Lewis, 1914): the sum of the difference between the $R$ and $S$ amplitudes in lead $I$ and the $S$ and $R$ amplitudes in lead $III$.
- $R_{avL}$ (Sokolow and Lyon, 1949): amplitude of $R$ wave in lead $avL$.
- $QRS\ area_{avL}$: the area under the $QRS$ complex in lead $aVL$.
- Systolic Pressure: physiological measure contained in the database.
- $QRS\ area_I$: the area under the $QRS$ complex in lead $I$.
- $S_{III}$: amplitude of the $S$ wave in lead $III$.

When a criterion is satisfied, the ECG is classified as LVH. All criteria require threshold which separates LVH and normal ECGs. The threshold is determined with the help of the ROC curve, which is a technique to visualize, organize and select classifiers based on their performance (Fawcett, 2006). In this kind of two dimensional plot, the Y axis is the True Positive Rate and the X axis is the False Positive Rate. We have chosen the threshold which satisfies a false positive rate of 25% (specificity of 75%). This step is not necessary for the criteria proposed in the literature because the thresholds are already defined.

## 2.3 Score Fusion

The original method proposed in this paper consists in fusing the methods explained earlier generating a single score which is used to assess LVH. The fusion strategy is based on the number of criteria which exceeds the thresholds found on the previous step. This way, the score is a number that represents the probability that patient has LVH.

# 3 EXPERIMENTS

## 3.1 Database

The database used is a subset of the MONICA2 Database that follow the guidelines established by the WHO MONICA Project (The World Health Organization MONICA Project: monitoring trends and determinants in cardiovascular diseases) (Tunstall-Pedoe et al., 1994).

The study sample was chosen after a random selection of householders in 1999, when 2068

subjects were invited to participate in the study, from a population of 142,913 people of both genders with ages ranging from 25 to 64 years. From the selected subjects, 1661 agreed to participate in the study and went to the *Hospital Universitário Cassiano Antonio Moraes* in Vitória, Brazil, for clinical and laboratory examination, so that the prevalence of cardiovascular risk factors could be determined.

In 2004 and 2005, these subjects were recruited again for the continuation phase of the WHO MONICA Project in Vitoria and underwent repeat clinical and laboratory evaluation, in addition to echocardiographic examination. From the initial sample, 652 agreed to participate in the second phase of the study.

The study published in (Angelo et al., 2007) creates a subsample of normal subjects and realizes a study of the LVMI (calculated through the echocardiogram) in this group of healthy subjects. The results show that the upper limit for the LVMI (defined by the 95% percentile) are:

- LVMI = 46.6 for the complete subset,
- LVMI = 46.4 for the female subset,
- LVMI = 47.7 for the male subset.

This way, patients with LVMI beneath those values are considered normal. The subset used in this paper is composed by 50 male subjects without any kind of heart block, where 25 subjects have LVMI greater than 47.7 and the other 25 subjects have LVMI smaller than it. The subjects were selected randomly following the requirement that the age of the two groups were as close as possible (normal: $(\mu, \sigma) = (58.73, 10.15)$ and LVH: $(\mu, \sigma) = (59.27, 8.99)$). This way differences in the age wouldn't compromise the analysis of the clinical data.

## 3.2 Results and Discussion

First of all, we have assessed the performance of each LVH criteria separately, as follows:

1. ROC curve: employing the ROC curve method, we have analyzed the cost (False Positive Rate, also shown as $1 - specificity$) and the benefit (True Positive Rate or sensibility) of the classifier. An example of a ROC curve is shown in Figure 1.
2. Hypothesis test for separable groups: it was carried out a paired t-test with the null hypothesis that the difference between the normal and the LVH groups (y-x) is a zero-

mean normal distribution. If the hypothesis is accepted with significance level of 5%, the groups are non-separable.

Table 1 presents the results of the area under de ROC curve (AUC) as well as the p-value for the hypothesis test for separable groups. We observe the best criteria for group separation are those related to the QRS amplitude or duration. Thus, it is clear that LVH causes much larger changes in the QRS complex than in other ECG waves. It is also evident that the features with lower p-value have higher AUC, showing that they are good for group separation, as expected.
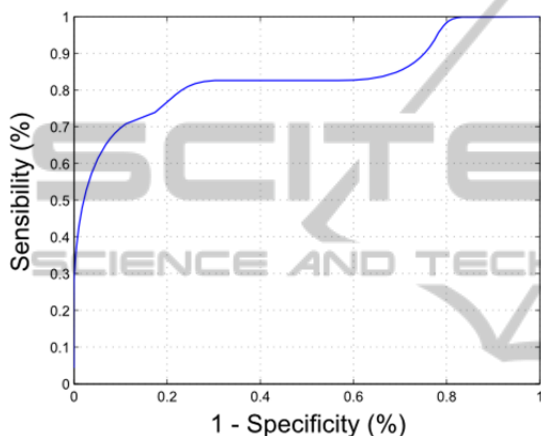


Figure 1: ROC Curve for the method proposed in (Grant, 1957).

Table 1: Best ten LVH criteria sorted from the highest AUCs (area under the ROC curve), which p-value indicates difference between normal and LVH groups.

| Feature | AUC | p-value |
|---|---|---|
| $(R + S)_{in\ any\ precordial\ lead}$ (Grant, 1957) | 0.82 | <0.001 |
| $(R_I + S_{III})$ (Gubner and Ungerleider, 1943) | 0.81 | <0.001 |
| $(R_I - S_I) + (S_{III} - R_{III})$ (Lewis, 1914) | 0.81 | <0.005 |
| $R_{avL}$ (Sokolow and Lyon, 1949) | 0.80 | <0.005 |
| $R_I$ (Gubner and Ungerleider, 1943) | 0.79 | <0.001 |
| $(largest\ R\ or\ S)_{in\ V1-V6} \times t_{QRS}$ (Mazzaro et al., 2008) | 0.78 | <0.001 |
| $S_{III}$ | 0.77 | <0.005 |
| $QRS\ area_{avL}$ | 0.76 | <0.005 |
| $QRS\ area_I$ | 0.74 | <0.005 |
| Systolic Blood Pressure | 0.74 | <0.005 |

Actually, the list of LVH criteria is bigger than the one of Table 1. In fact, we have tested forty

different criteria, employing the features discussed in the previous section. Considering all the tested criteria, we carried out the score fusion for LVH classification. The score fusion method can be configured according to a sensibility or specificity goal. In this article, we have selected two different goals: high sensibility or high specificity. Our results of score fusion are presented in Table 2, together with the results obtained by Mazzaro (2008), who uses a database of 1200 patients.

Table 2: Performance for LVH detection of several methods.

| Method | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|---|---|---|---|
| Romhilt-Estes | 16.3 | 95.8 | 66.7 |
| Sokolow-Lyon | 13.4 | 96.8 | 66.3 |
| Cornell voltage | 18.8 | 96.8 | 68.3 |
| Cornell duration | 22.2 | 96.0 | 69.0 |
| Perugia | 38.6 | 89.6 | 71.0 |
| Mazzaro | 35.2 | 88.7 | 68.7 |
| Score > 10 | 82.6 | 69.6 | 60.3 |
| Score > 18 | 69.7 | 95.6 | 62.3 |

From Table 2, we observe that the fusion score developed here improves sensitivity and specificity. While the criterion Romhilt-Estes shows sensitivity of only 16.3% for a specificity of 95.8%, this work (using the score equal to 18, for example) achieved specificity of 95.6% and sensitivity of 69.7%, far higher than the previous method.

The accuracy of the criteria presented by Mazzaro (2008) is higher than the accuracy of the score presented here, because the database there used has much more normal than LVH patients (higher specificity rates result in higher accuracy rates). A meaningful difference in methodology between this work and (Mazzaro, 2008) is that the system implemented here, from ECG segmentation till LVH classification, is fully automatic.

## 4 CONCLUSIONS

In this article, we presented a system for LVH classification from 12-lead ECG records. A set of features extracted from the ECG signal were used as input for our classifier. Our experiments considered different LVH criteria, most of them based on ECG features. The gold standard for LVH classification was the mass of the left ventricle obtained by

echocardiography examination, indexed to patient height raised to 2.7 ($h^{2.7}$).

Our experiments pointed out that the features that best correlate with LVMI are the ones related to the QRS complex amplitude and duration. Moreover, we have proposed a score which is based on combination of results of several criteria. The performance of our score was greater than the criteria used by experts, with specificity and sensitivity equal to 95.6% and 69.7%, respectively.

As future work, we plan to test our system in a bigger database, in order to confirm the consistency of our results. Furthermore, it would be interesting to conduct a physiological analysis of the results presented here to explain the reasons why those ECG waves or features are modified by LVH. Finally, our algorithm will be tested in a telecardiology project where abnormal ECGs will be prioritized to have a report from the cardiologist.

## ACKNOWLEDGEMENTS

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