# Twelve Dimensional Vectorcardiography. Is More Better?

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## Abstract

*Vectorcardiography (VCG) is generated by projecting signals from several leads onto three main orthogonal axes. There is evidence that by doing this projection, some relevant diagnostic information may be lost.*

*We investigated a new way to reduce this information loss. For that, we computed VCG features from the standard 12-lead ECG system and compared its performance in diagnosing myocardial infarction with the standard Frank's VCG, a VCG derived from the 12-lead ECG using the Dower's inverse transform and with a 3-dimensional projection of the 12-lead ECG obtained with principal component analysis. Although the results are not conclusive, they suggest that the proposed 12-dimensional VCG may reduce the information loss by preserving all the ECG leads without the need of any projection.*

## 1. Introduction

Vectorcardiography (VCG) is a way to represent the electrical forces generated by the heart by means of a vector in a three-dimensional orthogonal coordinate system. The orthogonal Frank's 3-lead VCG is considered as the standard for VCG [1][2] and is known for using three leads compared to the standard 12-lead ECG, which is the standard system used in the clinical practice.

However, the standard 12-lead ECG is characterized by a certain degree of redundancy, due to the fact that some of the leads are nearly aligned or derived as linear combinations of other leads. This redundancy already suggests that it is possible to reduce the number of leads by means of a projection or by selecting a subset of leads. Nonetheless, the question remains about if by reducing the number of leads (even if there is some redundancy in them), we lose relevant diagnostic information as well. There are already some authors indicating that lead projections and transformation functions have associated an information loss [3].

The aim of this research is to shed light about whether adding more leads (more information) will reduce the information loss and improve the diagnostic accuracy. In order to assess that, we considered four different approaches, each one having a different number of leads. A model is built for each approach by using VCG features coming from the corresponding lead system, and performance is evaluated in terms of the ability of each approach in classifying myocardial infarction (MI) vs healthy control (HC) subjects.

## 2. Materials and Methods

### 2.1. Database

We used the PhysioNet PTB Diagnostic ECG database (PTBDB) as data source [4][5]. This database contains 15 simultaneous ECG recordings (12-lead ECG and three Frank orthogonal leads) for 268 patients having different cardiac diseases. Table 1 shows the different diagnostic classes for the subjects in the PTBDB. The recordings were typically of ~2 min duration and all the signals were recorded for at least 30 seconds. The sample frequency of the recordings is 1KHz and we applied a bandpass filter between 0.5 Hz and 50 Hz in order to remove baseline wandering and high frequencies components.

Table 1. Diagnostic class of patients in the PTBDB.

| Diagnostic class | Number of subjects |
|---|---|
| Myocardial infarction | 148 |
| Cardiomyopathy/Heart failure | 18 |
| Bundle branch block | 15 |
| Dysrhythmia | 14 |
| Myocardial hypertrophy | 7 |
| Valvular heart disease | 6 |
| Myocarditis | 4 |
| Miscellaneous | 4 |
| Healthy controls | 52 |

In our research we considered only MI and HC subjects, having in total 200 patients.

### 2.2. Vectorcardiography

In order to assess what is the impact on having more leads (more information), we computed VCG features with four different approaches. One of those approaches, computes features from a 12-dimensional VCG while the other three compute features from a 3-dimensional VCG.

The VCG features were computed from the following systems:

1. **Frank 3-Lead VCG (VCG$_{Frank}$)**. This is the standard Frank's VCG. This available in the PTBDB.
2. **Dower's Inverse Transform VCG (VCG$_{Dower}$)**. We used the transformation matrix developed by Dower et al [6][7] that derive the 3-lead Frank VCG from the standard 12-lead ECG based on Frank's torso model.
3. **PCA-VCG (VCG$_{PCA}$)**. We built a three-dimensional VCG by projecting the standard 12-lead ECG into a three-dimensional space by using principal component analysis (PCA).
4. **Twelve Dimensional VCG (VCG$_{12D}$)**. In that case, we derived a 12-dimensional VCG from the standard 12-lead ECG. It was constructed by creating a twelve dimensional vector using the 12-lead ECG signals ($\vec{v}_{12D} = \{ecg_1, ecg_2, \ldots, ecg_{12}\}$). From this vector we derived the set of features described in section 2.3.

## 2.3. Feature Extraction

From each system described in Section 2.2, we extracted the following VCG features:

- Perimeter of the loop.
- Distance between the starting and end points of the loop.
- Coordinates of the maximum vector of the loop.
- Loop maximum vector length.
- Loop area.
- Area under each dimensional component. With dimensional component we refer to a single lead signal. For the case of 3-dimensional VCGs (VCG$_{Frank}$, VCG$_{Dower}$ and VCG$_{PCA}$) we have *x, y* and *z* components while for the case of the 12-dimensional VCG we have $ecg_1$ to $ecg_{12}$ components.
- Coordinates of the centroid of the loop.
- Loop centroid norm.

We extracted those features for both, QRS and T-wave loops of the cardiac cycle.

It is important to notice that for the case of the features related to vectors (maximum vector and centroid), we will get three features (*x, y* and *z* components of the vector) for the QRS and another three features for the T-wave when working with VCG$_{Frank}$, VCG$_{Dower}$ and VCG$_{PCA}$. When working with VCG$_{12D}$ we will get twelve features ($ecg_1$ to $ecg_{12}$ components of the vector) for the QRS and another twelve features for the T-wave. The same will occur for the case of the area under each dimensional component. Overall, we will have 54 more features in the case of VCG$_{12D}$ respect to the case of VCG$_{Frank}$, VCG$_{Dower}$ and VCG$_{PCA}$.

## 2.4. Models and Feature Selection

Before building any model and to reduce chances of overfitting, we divided the dataset into a training dataset containing 70% of the subjects (selected at random) and a validation dataset containing the remaining 30% of the subjects. For integrity purposes, we checked that the percentage of MI and HC subjects was the same in both training and validation datasets.

To assess the performance of each individual feature in diagnosing MI vs HC subjects, we used univariate logistic regression model. We did that for each of the VCG methods (VCG$_{12D}$, VCG$_{PCA}$, VCG$_{Dower}$ and VCG$_{Frank}$). The reason of using univariate logistic regression instead of multivariate logistic regression, is because we wanted to reduce any potential benefit of the 12-dimensional VCG (having more leads and also more features) when using a multivariate model. Therefore, we decided to compare the models using the best feature of every VCG method. The criteria to choose the best feature was:

- Having the feature in the logistic regression model a p-value $<0.05$.
- Having the feature the biggest area under the ROC curve (AUC) in the validation dataset.

We were interested as well, in the classification performance of the different VCG methods when using a multivariate model. We used lasso regression model [8] which is a multivariate extension of the logistic regression model that performs both variable selection and regularization. This enhances the prediction accuracy and the interpretability of the statistical model that its produces. In that case, we considered all parameters as initial input for all the approaches (VCG$_{12D}$, VCG$_{PCA}$, VCG$_{Dower}$ and VCG$_{Frank}$). The performance criterion we used in this case was the biggest AUC in the validation dataset after training the model.

# 3. Results and Discussion

## 3.1. Univariate Logistic Regression

Figure 1 shows the results of classifying MI vs HC subjects using the univariate logistic regression approach with the best feature for all approaches. The AUC values depicted in Figure 1 are obtained in the validation dataset (30% of the subjects) after training the model with 70% of the subjects.

Table 2 shows the best feature for each of the VCG methods. Note that the best feature of VCG$_{Frank}$ and VCG$_{Dower}$ is the same. This is not a surprise as VCG$_{Dower}$ is a reconstruction of the VCG$_{Frank}$ from the 12-lead ECG. Also, AUC performance results for both are similar (see

Figure 1) which can be also explained in the same way as above. Also, we showed in a previous work [9] that Frank's VCG and Dower's VCG were having similar performance in classifying MI and HC subjects.

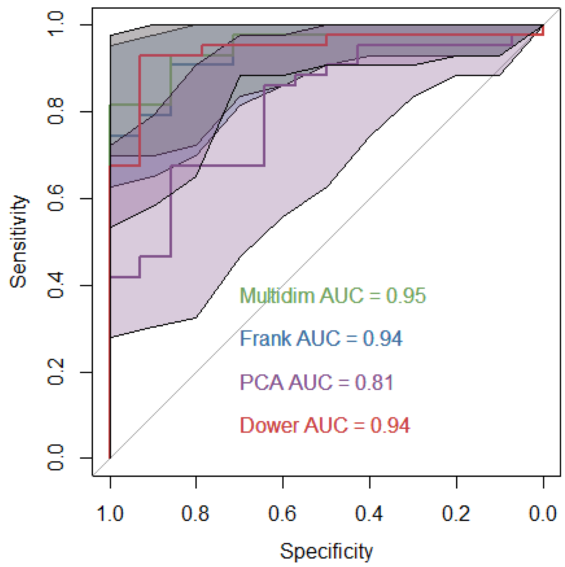


Figure 1. AUC performance for the univariate logistic regression method when classifying MI vs HC subjects. $VCG_{12D}$ (green), $VCG_{Frank}$ (blue), $VCG_{PCA}$ (purple) and $VCG_{Dower}$ (red).

Table 2. Best feature selected using univariate logistic regression for the different VCG methods.

| VCG | Feature |
|---|---|
| $VCG_{12D}$ | T-wave average vector length on the 4th dimensional component. |
| $VCG_{Frank}$ | T-wave average vector length on x direction. |
| $VCG_{PCA}$ | QRS standard deviation on x component of the centroid. |
| $VCG_{Dower}$ | T-wave average vector length on x direction. |

It is interesting to see that $VCG_{12D}$, $VCG_{Frank}$ and $VCG_{Dower}$ methods selected as best feature a T-wave parameter while $VCG_{PCA}$ method selected a QRS parameter. We believe this is due to the fact that PCA method gets the highest energetic modes of the signal being those associated to the QRS part of the cardiac cycle. This may explain the relatively poor performance of PCA VCG (when compared with the other VCG methods) as it has been shown in the literature that the T-wave component of the cardiac cycle contains the most relevant information related to the diagnosis of MI [10][11].

As can be observed in Figure 1, the approach which gives the best results is the one based on the 12-lead ECG, closely followed by Frank VCG and Dower's VCG, being PCA-VCG the one that is performing the worst. Nonetheless, as depicted in Table 3, the difference between 12-lead, Frank's and Dower's VCGs are not significant while it is significant when comparing 12-lead and Dower's VCGs against PCA-VCG.

Table 3. DeLong's significant test for VCG AUC values using univariate logistic regression method.

| ROC-Test | p-value |
|---|---|
| $VCG_{12D}$ vs $VCG_{Frank}$ | 0.62 |
| $VCG_{12D}$ vs $VCG_{Dower}$ | 0.82 |
| $VCG_{12D}$ vs $VCG_{PCA}$ | 0.03 |
| $VCG_{Frank}$ vs $VCG_{PCA}$ | 0.05 |
| $VCG_{Dower}$ vs $VCG_{PCA}$ | 0.04 |
| $VCG_{Frank}$ vs $VCG_{Dower}$ | 0.91 |

## 3.2. Multivariate Lasso

Figure 2 shows the results when using a multivariate lasso model. Once again, we see that the best approach is the one based on the 12-leads, closely followed by Dower's and Frank's approaches, being PCA approach the one with the lowest performance. However, when looking to significance in performance among the different VCGs (Table 4), we see that the differences are not significant.

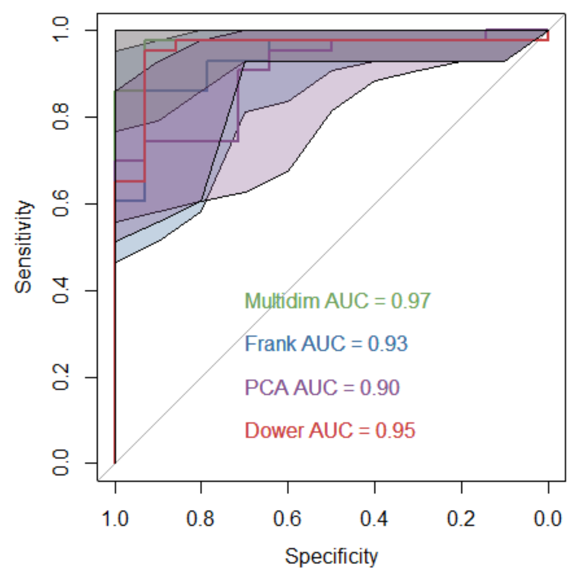


Figure 2. Lasso AUC for classifying MI vs healthy control subjects using $VCG_{12D}$ (green), $VCG_{Frank}$ (blue), $VCG_{PCA}$ (purple) and $VCG_{Dower}$ (red).

Table 5 shows the number of features selected for every VCG method. We see that 12-dimensional VCG is the one that is having a greater number of features selected in the lasso model. On the other hand, Frank, Dower, and PCA VCGs are having the same number of features selected by lasso method. This makes sense since $VCG_{12D}$ has 54 more features than $VCG_{Frank}$, $VCG_{Dower}$ and $VCG_{PCA}$, so seems normal that the lasso method selected more features for the case of $VCG_{12D}$.

Table 4. DeLong's significant test for VCG AUC values using lasso method.

| ROC-Test | p-value |
|---|---|
| $VCG_{12D}$ vs $VCG_{Frank}$ | 0.08 |
| $VCG_{12D}$ vs $VCG_{Dower}$ | 0.29 |
| $VCG_{12D}$ vs $VCG_{PCA}$ | 0.10 |
| $VCG_{Frank}$ vs $VCG_{PCA}$ | 0.53 |
| $VCG_{Dower}$ vs $VCG_{PCA}$ | 0.21 |
| $VCG_{Frank}$ vs $VCG_{Dower}$ | 0.82 |

Table 5. Number of features selected for the different VCG methods when using Lasso.

| VCG | # Features |
|---|---|
| $VCG_{12D}$ | 17 |
| $VCG_{Frank}$ | 10 |
| $VCG_{PCA}$ | 11 |
| $VCG_{Dower}$ | 11 |

If we compare the AUC performance between the univariate logistic regression method (Figure 1) and the multivariate lasso method (Figure 2), we see that the improvement in the case of multivariate lasso method is limited (~ 2.8% AUC increase in average). We believe that the main reason for this is that the classification task of differentiate between MI and HC subjects is a not complex one. Therefore, with one feature (the best feature in the univariate method), we can explain most of the variance of the problem and adding additional features will not increase the classification performance significantly.

## 4. Conclusions

Having more ECG leads will add certain degree of redundant information. This is especially true for the case of the standard 12-lead ECG in which some of the leads are nearly aligned or derived as linear combinations of other leads. Nonetheless, still the question remains whether we just can remove some of the leads in the hope of getting the same performance and using less leads.

In this study we investigated the ability of VCG features to distinguish between MI patients and healthy subjects, when those features are extracted from three or more leads. Results showed that when VCG parameters are computed on 12-leads, rather than only three, classification performance increases. Nonetheless the differences in performance were not significant and not conclusive results could be derived from our research. One possible explanation for not having significant differences is that the classification problem we chose (MI vs HC subjects) was easy enough to make the three-dimensional VCGs perform well in comparison with the 12-dimensional VCG. If the classification task is not very difficult, a good classification performance can be achieved without the need of lot of information and then the information loss will not play a significant role. This may explain as well why the univariate logistic regression model (1 feature model) performed almost as good as the multivariate lasso (multiple feature model). From that, we can conclude that when it comes to separate between MI and HC, we do not need all the information present in the 12-leads and selecting the best parameter in one of the leads is enough to achieve an AUC above 93%.

Additionally, we believe that having a more challenging classification problem may increase differences in performance as information loss will play a more critical role. More research has to be done in order to validate this hypothesis.

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