FINDING NEW EASI ECG COEFFICIENTS
Improving EASI ECG Model using Various Regression Techniques

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Abstract: Main idea of this study was to increase efficiency of the EASI ECG method introduced by Dover in 1988 using various regression techniques. EASI was proven to have high correlation with standard 12 lead ECG. Apart from that it is less susceptible to artefacts, increase mobility of patients and is easier to use because of smaller number of electrodes. Multilayer Perceptron (Artificial Neural Network), Support Vector Machine Regression (with Sequential Minimal Optimization algorithm), Linear Regression and Pace Regression methods were used to improve the quality of the 12-lead electrocardiogram derived from four (EASI) electrodes. Hundreds of ANNs with different learning rates and number of hidden layers were built and tested using data from PhysioNet and also data that were artificially generated. Next SMO Regression method with few different kernels (polynomial, normalized polynomial and RBF), Linear Regression and Pace Regression method were tested on the same dataset. All computed results were compared with those obtained using classic EASI ECG method described by Dover. Computation of Root Mean Squared Error and Correlation Coefficient was performed to measure the overall result of a given method. Obtained results show that various regression methods could be used to increase the performance of EASI ECG method and thus make it more popular.

1 INTRODUCTION

In 1988 Dower and his team introduced EASI ECG system, which derives standard 12 lead ECG using only 5 electrodes. The E electrode is on the sternum while, the A and I electrodes are at the left and right mid-auxiliary lines, respectively. The S electrode is at the sternal manubrium. The fifth electrode is a ground and is typically placed on one or the other clavicle, see Fig 1. EASI was proven to have high correlation with standard 12 lead ECG, as well as with Mason-Likar 12-Lead ECG. Apart from that it is less susceptible to artifacts, it increase mobility of patients, it is easier and faster to use because of smaller number of electrodes. What is more, smaller number of electrodes reduces cost of a device. The electrodes are positioned over readily identified landmarks which can be located with minimal variability, independent of the patient's physique, assuring high repeatability. The electrode placement make the chest largely unencumbered, allowing physical or imaging examination of the heart and lungs without removing the electrodes.

2 PROBLEM DESCRIPTION

In the classical approach introduced by Dower, using the EASI lead configuration, 3 modified vectorcardiographic signals are recorded from the following bipolar electrode pairs:

- A-I (primarily X, or horizontal vector component)
- E-S (primarily Y, or vertical vector component)
- A-S (containing X, Y, plus Z, the anteriorposterior component)

Each of the 12 ECG leads is derived as a weighted linear sum of these 3 base signals using the following formula:

$$L_{derive} = a(A - I) + b(E - S) + c(A - S) \qquad (1)$$

where L represents any surface ECG lead and a, b, and c represent empirical coefficients. These coefficients, developed by Dower, are positive or negative values, accurate to 3 decimal places, which result in leads very similar to standard leads.

Our idea to improve EASI ECG performance was to find new model used for 12 ECG leads calculation. To do that we treated the system as a black box with 4 input variables: E, A, S, I and 12

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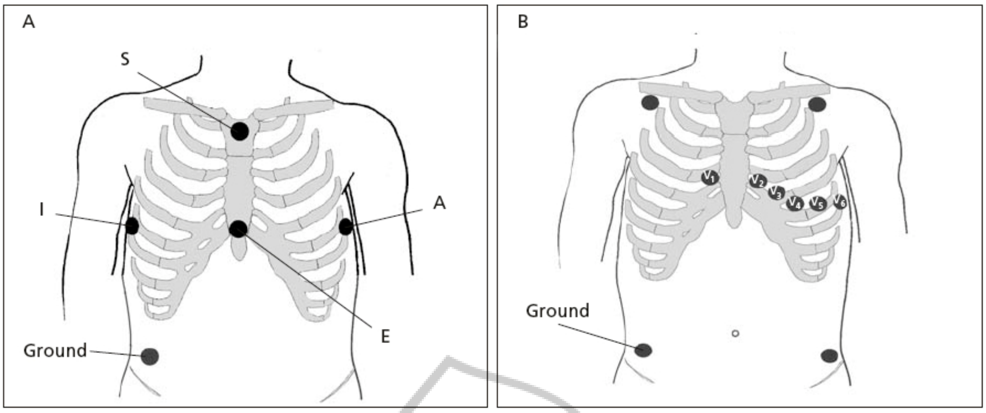

Figure 1: Lead placement for the EASI system (A) and the Mason-Likar (B) 12-lead electrocardiogram.

output variables: I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6 and we used various regression techniques to build a model.

3 USED METHODS

Four different regression methods were tested to find a best fitting model, namely Artificial Neural Network (ANN), Support Vector Regression with Sequential Minimal Optimization algorithm used, Linear Regression and Pace Regression.

3.1 Artificial Neural Network

ANN is a system inspired by the operation of biological neural networks, in other words, is an emulation of biological neural system. We used Multilayer Perceptron (MLP) to build the model. The Multilayer Perceptron method was proven by the Cybenko theorem to be a universal function approximator. It uses a backpropagation technique to train the network. In our experiments MLP used a sigmoid activation function:

$$\phi(y_i) = (1 + e^{-v_i})^{-1} \tag{2}$$

where y_i is the output of the ith node (neuron) and v_i is the weighted sum of the input synapses. Activation function determine whether or not a neuron fires. The multilayer perceptron consists of three or more layers (an input and an output layer with one or more hidden layers) of nonlinearly-activating nodes. Each node in one layer connects with a certain weight w_{ij} to every node in the following layer. Learning in the network is done by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result. To obtain the best model hundreds of different networks were built, with different values of learning rate and various number of hidden layers (nodes).

3.2 Support Vector Regression

The Support Vector algorithm is a nonlinear generalization of the Generalized Portrait algorithm developed in Russia in the sixties. As such, it is firmly grounded in the framework of statistical learning theory, or VC theory, which has been developed over the last three decades by Vapnik and Chervonenkis. Due to this industrial context, SV research has up to date had a sound orientation towards real-world applications. Initial work focused on OCR (optical character recognition). Within a short period of time, SV classifiers became competitive with the best available systems for both OCR and object recognition tasks. We tested three kernels for SV regression:

- The RBF kernel.
- The polynomial kernel.
- The normalized polynomial kernel.

3.3 Linear Regression

The next regression technique used was a classic linear regression. In general this technique fits a linear model to a set of data. Because the model generated is a linear model this approach is simple and easy to use, which makes this approach extensively used in practical applications.

3.4 Pace Regression

Last method used was Pace Regression method. Pace Regression improves on classical ordinary least squares (OLS) regression by evaluating the effect of each variable and using a clustering analysis to improve the statistical basis for estimating their contribution to overall regression. As well as outperforming OLS, it also outperform – in a remarkably general sense – other linear modelling techniques in the literature, including subset selection procedures, which seek a reduction in dimensionality that falls out as a natural byproduct of pace regression.

4 RESULTS

4.1 Improved Model

Based on results obtained from all tested methods one linear model was generated:

$$aVF = 0.2143 \times \mathrm{E} + 0.1146 \times \mathrm{A} -1.0935 \times \mathrm{S} + 0.7287 \times \mathrm{I} - 3.0685 \quad (3)$$

$$aVL = -0.1298 \times E + 0.5988 \times S -1.6804 \times I + 2.3043 \quad (4)$$

$$aVR = -0.0845 \times E - 0.1195 \times A + 0.4929 \times S + 0.9408 \times I + 0.7811 \quad (5)$$

$$I = -0.0302 \times E + 0.083 \times A + 0.0718 \times S - 1.7402 \times I + 1.0043 \quad (6)$$

$$II = 0.1992 \times E + 0.1561 \times A - 1.0576 \times S - 0.1414 \times I - 2.5664 \quad (7)$$

$$III = 0.2295 \times E + 0.0731 \times A - 1.1295 \times S + 1.5988 \times I - 3.5707 \quad (8)$$

$$V1 = 0.6344 \times E + 0.0799 \times A + 0.501 \times S + 0.4933 \times I + 4.0389 \quad (9)$$

$$V2 = 1.0836 \times E - 0.095 \times A + 0.5252 \times S - 1.249 \times I + 13.6635 \quad (10)$$

$$V3 = 0.7993 \times E + 0.2801 \times A + 0.0881 \times S - 2.3115 \times I + 5.0573 \quad (11)$$

$$V4 = 0.368 \times E + 1.2349 \times A + 0.0869 \times S - 1.1872 \times I - 2.2414 \quad (12)$$

$$V5 = 0.1384 \times E + 1.5578 \times A + 0.0865 \times S + 0.3616 \times I + 0.024 \quad (13)$$

$$V6 = 0.0362 \times E + 1.2552 \times A - 0.1469 \times S + 0.706 \times I - 1.2352 \quad (14)$$

4.2 Results Comparison

Each model calculation was 10 fold cross validated. All results are based on data from PhysioNet database and also on data that were artificially generated according to the following equations (described in the paper "Investigation Of A Transfer Function Between Standard 12-Lead ECG And EASI ECG"):

$$\mathrm{E} = 6.4073889 \times \mathrm{II}\ 4.58091464 \times \mathrm{aVR} + 4.4236590 \times \mathrm{aVF} + 1.4023342 \times \mathrm{V1} - 0.2316670 \times \mathrm{V2} + 0.63803224 \times \mathrm{V3}\ 0.3104148 \times \mathrm{V4}\ 0.5253245 \times \mathrm{V5} + 0.7453142 \times \mathrm{V6} \quad (15)$$

$$\mathrm{A} = 0.1205489 \times \mathrm{I} + 0.1440902 \times \mathrm{aVL}\ 0.07460267 \times \mathrm{V1} - 0.005248586 \times \mathrm{V2} + 0.04413031 \times \mathrm{V3}\ 0.001846735 \times \mathrm{V4} + 0.14529887 \times \mathrm{V5} + 0.5326776 \times \mathrm{V6} \quad (16)$$

$$\mathrm{S} = 0.9615144 \times \mathrm{II} + 0.07950829 \times \mathrm{aVL} + 0.21000511 \times \mathrm{aVF} - 0.096557012 \times \mathrm{V1} + 0.3608502 \times \mathrm{V2}\ 0.32692627 \times \mathrm{V3} + 0.252434208 \times \mathrm{V4} + 0.04650518 \times \mathrm{V5}\ 0.1318653 \times \mathrm{V6} \quad (17)$$

$$\mathrm{I} = 0.1494002 \times \mathrm{I}\ 0.24593780 \times \mathrm{aVL}\ 0.003465868 \times \mathrm{V1} - 0.1516211491 \times \mathrm{V2} + 0.2637671 \times \mathrm{V3}\ 0.17090946 \times \mathrm{V4} + 0.03756737 \times \mathrm{V5}\ 0.10936146 \times \mathrm{V6} \quad (18)$$

Calculated models were compared with results obtained using classical Dower approach and also with Improved EASI Coefficients described in the paper "Improved EASI Coefficients: Their Derivation, Values, and Performance" by Dirk Q. Feild, Charles L. Feldman, and B. Milan Horacek. To determine performance of all systems, for each of them correlation coefficient (Table 1) and root mean squared error (Table 2).

4.3 Tables

Table 1: Correlation coefficients comparison.

	Obtained Model	EASI Dower approach	Improved EASI Coefficients
aVF	0,939	0,984	0,776
aVL	0,966	0,955	0,922
aVR	0,984	0,985	0,966
I	0,985	0,971	0,973
II	0,964	0,994	0,894
III	0,941	0,963	0,786
V1	0,99	0,882	0,849
V2	0,984	0,968	0,872
V3	0,975	0,971	0,751
V4	0,971	0,981	0,851
V5	0,992	0,977	0,97
V6	0,997	0,888	0,985

Table 2: Root Mean Squared Error comparison.

	Obtained Model	EASI Dower approach	Improved EASI Coefficients
aVF	27,45	28,41	66,29
aVL	22,02	35,45	34,22
aVR	16,03	31,86	55,3
I	18,01	40,75	42,47
II	26,13	32,57	78,2
III	31,41	37,19	60,03
V1	21,01	99,24	86,42
V2	40,54	177,75	119,61
V3	46,62	120,25	141,69
V4	55,6	144,6	129,96
V5	24,66	119,93	49,9
V6	10,77	93,17	33,1

5 CONCLUSIONS

Above results show that the best performance was obtained for the linear model built using regression techniques. Second best model was one created by Dower. Surprisingly low performance was observed for model that uses improved EASI coefficients.

Further work in the topic of improving EASI ECG coefficient using various regression techniques should be continued.

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