Improving EASI ECG Method Using Various Machine Learning and Regression Techniques to Obtain New EASI ECG Model

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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), Linear Regression, Pace Regression and Bagging Predictors methods were used to improve the quality of the 12-lead electrocardiogram derived from four (EASI) electrodes.**

***Index Terms*—EASI, ECG, artificial neural network, linear regression, pace regression, bagging predictors.**

I. INTRODUCTION

In 1988 Dower and his team introduced EASI ECG system. It derives standard 12 lead electrocardiogram (ECG) and uses only 5 electrodes [1]. 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 it is typically placed on the one or on the other clavicle, see Fig. 1. EASI was proven to have high correlation with a standard 12 lead ECG [2], [3], [4], [5], as well as with Mason-Likar 12-Lead ECG [6]. Apart from that it is less susceptible to artifacts, it increases mobility of patients and it is also 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.

II. PROBLEM FORMULATION

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

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

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Each of the 12 ECG leads is derived as a weighted linear sum of these 3 base signals using the following formula: $L_{derive} = a(A-I)+b(E-S)+c(A-S)$, 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 [7]. 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 output variables: I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6 and we used various regression techniques to build a model.

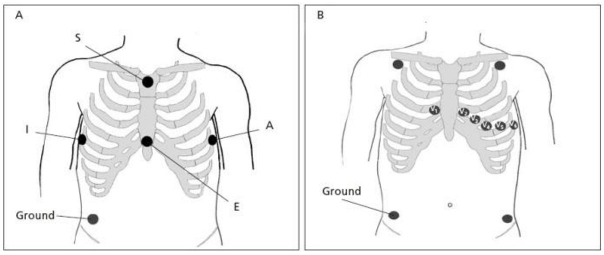

Fig. 1. Lead placement for the EASI system (A) and the Mason-Likar (B) 12-lead electrocardiogram.

III. USED METHODS

Four different methods were tested to find a best fitting model, namely Artificial Neural Network (ANN), Linear Regression, Pace Regression and Bagging Predictors.

A. 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, which uses a backpropagation technique to train the network. In our experiments MLP used a sigmoid activation function: $\phi(y_i) = (1+e^{-v_i})^{-1}$, where yi is the output of the ith node (neuron) and vi 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. This method of network learning is called supervised learning [8]. The Multilayer Perceptron method was proven by the Cybenko theorem to be a universal function approximator [9]. To obtain the best model hundreds of different networks were built, with different values of learning rate and various number of hidden layers (nodes).

B. Linear Regression

Linear regression is the oldest and most widely used predictive model. The method of minimizing the sum of the squared errors to fit a straight line to a set of data points was published by Legendre in 1805 and by Gauss in 1809. A linear regression model fits a linear function to a set of data points. The form of the function is:

$$Y = ß_0 + ß_1 * X_1 + ß_2 * X_2 + \ldots + ß_n * X_n$$

where Y is the target variable, X_1, X_2, …, X_n are the predictor variables, and $ß_1$, $ß_2$, …, $ß_n$ are coefficients that multiply the predictor variables. $ß_0$ is a constant.

If there is a single predictor variable X_1, then the function describes a straight line. If there are two predictor variables, then the function describes a plane. If there are *n* predictor variables, then the function describes an *n*-dimensional hyperplane.

If a perfect fit existed between the function and the actual data, the actual value of the target value for each record in the data file would exactly equal the predicted value. Typically, however, this is not the case, and the difference between the actual value of the target variable and its predicted value for a particular observation is the error of the estimate which is known as the "deviation" or "residual". The goal of regression analysis is to determine the values of the ß parameters that minimize the sum of the squared residual values for the set of observations. This is known as a "least squares" regression fit. It is also sometimes referred to as "Ordinary Least Squares" (OLS) regression [10].

C. Pace Regression

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 [11].

D. Bagging Predictors

Bagging predictors is a method for generating multiple versions of a predictor and using these to get an aggregated predictor. The aggregation averages over the versions when predicting a numerical outcome and does a plurality vote when predicting a class. The multiple versions are formed by making bootstrap replicates of the learning set and using these as new learning sets. Tests on real and simulated data sets using classification and regression trees and subset selection in linear regression show that bagging can give substantial gains in accuracy. The vital element is the instability of the prediction method. If perturbing the learning set can cause significant changes in the predictor constructed, then bagging can improve accuracy [12].

IV. Results

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

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

$$aVL = -0.1298 \times E + 0.5988 \times S - 1.6804 \times I + 2.3043$$

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

$$I = -0.0302 \times E + 0.083 \times A + 0.0718 \times S - 1.7402 \times I + 1.0043$$

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

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

$$V1 = 0.6344 \times E + 0.0799 \times A + 0.501 \times S + 0.4933 \times I + 4.0389$$

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

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

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

$$V5 = 0.1384 \times E + 1.5578 \times A + 0.0865 \times S + 0.3616 \times I + 0.024$$

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

V. Result Comparison

Each model calculation was 10 fold cross validated. All results are based on data from PhysioNet database [13] 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" [14]):

$$E = -6.4073889 \times II - 4.58091464 \times aVR + 4.4236590 \times aVF + 1.4023342 \times V1 - 0.2316670 \times V2 + 0.63803224 \times V3 - 0.3104148 \times V4 - 0.5253245 \times V5 + 0.7453142 \times V6$$

$$A = 0.1205489 \times I + 0.1440902 \times aVL - 0.07460267 \times V1 - 0.005248586 \times V2 + 0.04413031 \times V3 - 0.001846735 \times V4 + 0.14529887 \times V5 + 0.5326776 \times V6$$

$$S = -0.9615144 \times II + 0.07950829 \times aVL + 0.21000511 \times aVF - 0.096557012 \times V1 + 0.3608502 \times V2 - 0.32692627 \times V3 + 0.252434208 \times V4 + 0.04650518 \times V5 - 0.1318653 \times V6$$

$$I = -0.1494002 \times I - 0.24593780 \times aVL - 0.003465868 \times V1 - 0.1516211491 \times V2 + 0.2637671 \times V3 - 0.17090946 \times V4 + 0.03756737 \times V5 - 0.10936146 \times V6$$

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" [15]. To determine performance of all systems, for each of them root mean squared error (Table 1) were calculated. Obtained results are presented in three tables below. Performance of the regression based model is also shown on the plot, where it is compared with original ECG signal as well as with two other EASI based signals generated using classical Dower method and Improved EASI Coefficients method.

A. Plot

Plots of V1 (Fig. 2) signal measured using standard ECG method, derived using EASI method developed by Dower, Improved EASI Coefficients method [14] and our model.

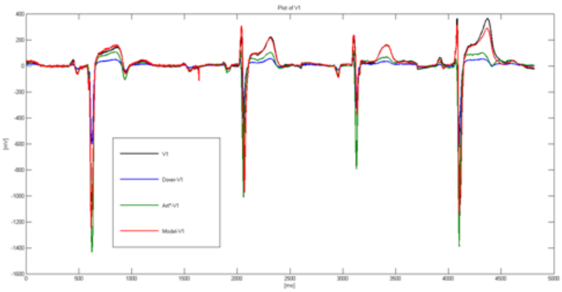

Fig. 2: Plot of measured and derived V1 signals.

B. Table

TABLE 1 - ROOT MEAN SQUARED ERROR RESULTS

	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	55.60	144.6	129.96
V5	24.66	119.93	49.9
V6	10.77	93.17	33.1

VI. CONCLUSION

Above results show that using various machine learning and regression techniques help to improve the basic EASI ECG model. The best performance was obtained for our linear model built using machine learning and regression techniques. It provides a significantly lower values of Root Mean Squared Error and Mean Absolute Error. Second best model was one created by Dower. Surprisingly low performance was observed for model that uses improved EASI coefficients described in the paper "Improved EASI Coefficients: Their Derivation, Values, and Performance" [15]. In the nearest future we plan a series of clinical trials on a group of volunteers, in which we want to compare a working EASI ECG system using our improved model with a standard ECG equipment.

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