# Novel Method for Deriving Vectorcardiographic Leads Based on Artificial Neural Networks

**M. Vozda, T. Peterek, M. Cerny**

FEECS, Department of Cybernetics and Biomedical Engineering, VSB – Technical University of Ostrava, Ostrava – Poruba, Czech Republic
Email: michal.vozda@vsb.cz

***Abstract.*** *Many methods for deriving vectorcardiographic (VCG) leads from 12-lead electrocardiogram (ECG) were published. All of them are based on a linear transformation. Differences are only in coefficients of transformation matrixes which are designed based on a model or on linear regression methods. This paper presents and assesses a new nonlinear transformation method based on artificial neural networks (ANNs) which offer better accuracy of the transformation. Derived VCG leads were compared with directly measured Frank leads for a group of 283 records from the PTB database. Methods based on ANNs achieve significantly lower MSE in all leads and significantly higher correlation coefficient in Z lead compared with both Kors and inverse Dower method.*

*Keywords: vectorcardiography, artificial neural network, Frank leads*

## 1. Introduction

The vectorcardiogram is the spatial representation of electromotive forces generated during cardiac activity and is analysed in three spatial planes (horizontal, frontal and sagittal). Although there are several VCG lead systems, in clinical practice they are not measured directly but usually derived from the 12-led ECG using some transformation method like inverse Dower [4] or Kors [5] method. Many methods for deriving VCG leads were developed. Modern methods try to minimalize the error of the transformation between lead systems. Most methods are based on linear transformation and the differences between them are in coefficients of transformation matrices. No nonlinear methods have been tested yet. There are some methods that can be used for solving nonlinear regression problems. The most popular methods are based on artificial neural network or support vector machine.

The purpose of this study is to present the nonlinear regression method based on ANNs for deriving VCG leads from the 12-lead ECG.

## 2. Subject and Methods

*Study Population*
We used the PTB diagnostic database that has been recorded on healthy volunteers and patients with different heart diseases at the Department of Cardiology of University Clinic Benjamin Franklin in Berlin, Germany. The database contains 549 records from 286 subjects (aged 17 to 87, mean 57.2; 209 men, mean age 55.5, and 81 women, mean age 61.6). Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6) together with the 3 Frank VCG leads (X, Y, Z). Each signal is digitized at 1000 samples per second, with 16-bit resolution over a range of ±16.384 mV [3].

Only the first records that excluded patients with pacemaker were taken into account. The records were band-passed by a FIR filter with linear phase response in band from 0.25 to 150 Hz (-3dB). From the filtered records representative beats were chosen; PVCs and artefacts were excluded. The beginning of the beat was defined as the distance from the R wave: $T_R - 0.4 \cdot T_{\min(RR)}$ and the end of the beat was defined as $T_R + 0.6 \cdot T_{\min(RR)}$, where $T_R$ is the time instant of an R wave and $T_{\min(RR)}$ is a minimal heart cycle in the record. Individual representative beats were averaged in each of the 15 leads. Averaging should improve the signal-noise ratio. In this way we obtained 283 representative beats in 15 leads.

*Design of Neural Network Architecture*

To synthetize VCG leads from the 12-lead ECG we use a multilayer feed-forward ANN trained by means of the supervised back-propagation algorithm. The architecture includes input layer, hidden and output layers. Each layer includes neurons with specific activation function.

ANNs with 1, 2, 3 and 4 hidden layers and different numbers of neurons in hidden layers were tested. ANN with 2 hidden layers and 4 neurons in each hidden layer achieved the best accuracy of transformation. With increasing number of layers and/or neurons increased the training time of ANN with insignificant impact on the accuracy of the transformation. The input layer contains 8 neurons. Input and hidden layers contain neurons with hyperbolic tangent sigmoid activation function. The output layer contains 3 neurons with linear activation function.

Committee machine method is popular in processing with neural networks. This method uses a divide and conquer strategy in which the responses of multiple ANNs are averaged into a single response. This method was used in similar application for deriving chest leads from quasi-orthogonal leads I, II and V2 in work [1]. We decided to compare the impact of this method on the accuracy of the transformation, too.

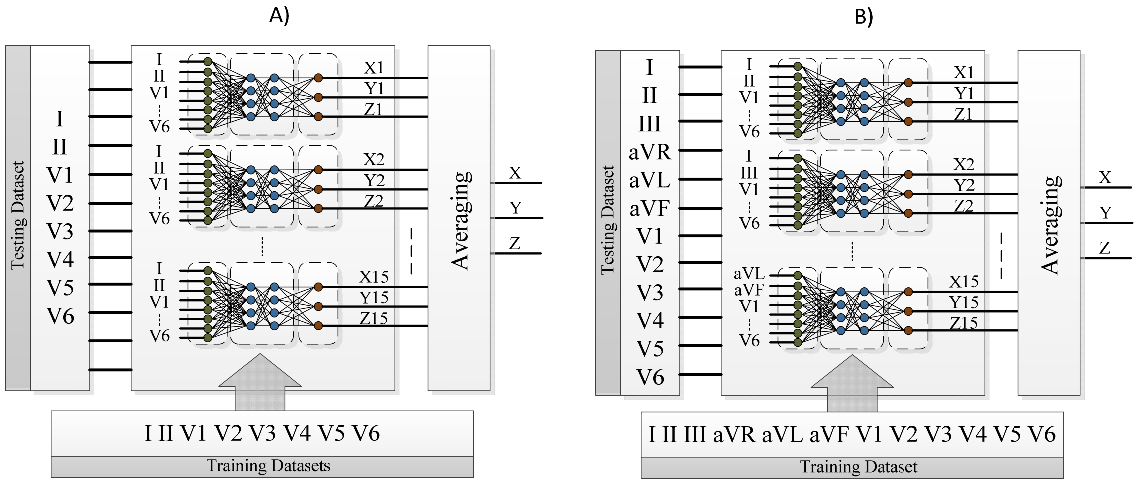


Fig. 1. Committee of ANNs for different training datasets A) and different ECG leads B).

*Tested Methods*

Four new and two commonly used methods were tested. ANN1 represents a method based on one ANN which is described above. The ANN is trained on all records from the training dataset. Its inputs are independent ECG leads which are usually used for transformations (I, II and V1…V6). ANN2 represents a method based on committee of 15 ANNs. Each ANN has 8 inputs represented by 8 independent ECG leads. Six of them are leads V1…V6 and the last two leads are some of the 15 combinations of limb leads pairs (I, II; I, III; I, aVL; … aVR, aVF). Each ANN has different combination of independent ECG leads what is shown in Fig.2B. ANN3 represents a committee of 15 ANNs. Each ANN is trained on slightly different training dataset in sense of cross validation (Fig. 2A). ANN4 represents a combination of methods ANN2 and ANN3. The committee includes altogether 75 ANNs. Fifteen different combinations of independent ECG leads were used for group of 5 ANNs which are trained on slightly different training datasets. All described methods were compared with the inverse Dower and the regression based Kors transformations which are commonly used in clinical and research practice [2].

*Verification and Validation*
All methods were tested under the same conditions, with the same testing datasets and with 10-folds cross validation. This approach is usually used for testing the performance of supervised learning-based methods. Records were randomly divided into 10 groups, 9 of them (255 records) served for training the ANNs as the training dataset. One remaining group (28 records) served for testing of all methods as the testing dataset. In the next step other 9 groups were chosen and 1 remaining group was again used as the testing dataset. We continued in this way 10 times. This is the most efficient way how to test the supervised learning-based methods with maximum usage of the training data.

Performance of all methods was evaluated by the two most often used parameters: Pearson correlation coefficient and Mean Squared Error (MSE) [1], [2]. Pearson correlation coefficient indicates the degree of similarity between two signals and is independent from the differences in their amplitudes. The MSE is a measure of differences in amplitudes between two signals. Each method was tested for all VCG leads. MSEs and correlations between leads computed by the tested methods and directly measured Frank leads were evaluated.

## 3. Results

One sample t-test was used for testing the normality of MSE and correlation coefficients for all methods and in all leads. Whereas that data are not from a normal distribution, the nonparametric Mann-Whitney U-test was used for testing the differences between the methods. The null hypothesis was tested that the data obtained from two compared methods are samples with equal medians. Rejecting the null hypothesis we prove statistical difference between the two methods at the 5% significance level ($\alpha = 0.05$).

The statistical tests prove that the differences between the methods based on ANNs are not significant. For all of them the MSE is for all leads significantly lower than for Kors and inverse Dower transformation. The correlation coefficient for methods with ANNs is significantly higher only for lead Z when compared with the Kors transform. Differences in correlations for X and Y leads are not significant. For the Kors method, the MSE is significantly lower for all leads and correlation coefficient is higher for leads X and Z when compared with the inverse Dower transformation.

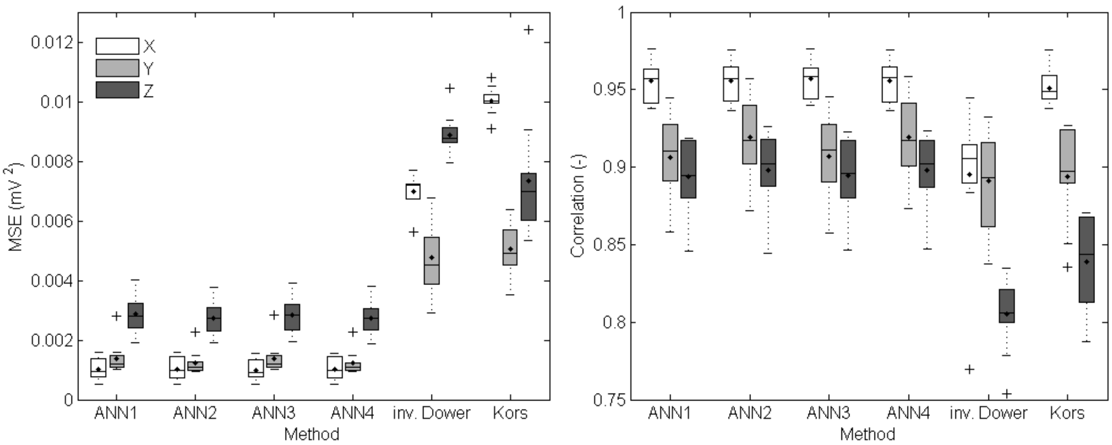


Fig. 2. Box-Whisker diagram of the MSE and correlation for individual methods in leads X, Y and Z.

## 4. Discussion

In this study, six transformation methods were tested and compared under the same conditions. Differences between methods based on ANN are insignificant and all of them are more accurate than both Kors and inverse Dower method that are commonly used. We validated that the Kors method achieves better accuracy when compared with the inverse Dower method what was shown also in other publications [2], [5]. Our results suggest that nonlinear regression method could improve the accuracy of transformation for the 12-lead vectorcardiography but for practical application its testing on a larger dataset is needed. In addition to the PTB database, it is possible to use CSE databases that include many 15-lead records.

Evaluation of a new method based on MSE and correlation is often used but it cannot replace the experience of a skilled cardiologist who can evaluate differences in diagnostic information which is the most important parameter. For future work we would like to test nonlinear regression methods on larger datasets measured in cooperation with cardiologists at different workplaces. Further, we would like to test the performance of transformation methods based on features that are commonly used in vectorcardiography, like QRST or planar angle.

## 5. Conclusions

The 12-lead vectorcardiography is based on transformations of the 12-lead ECG to VCG leads. Each transformation introduces certain error of amplitude and shape of the derived VCG leads. In this article we proposed a new method based on ANNs that provides significantly higher accuracy of transformation when compared with conventional commonly used methods. Methods based on ANNs can improve the state of the art in transformations between lead systems.

**Acknowledgements**

The work and the contributions were supported by the project SV SP2014/194 “Biomedical engineering systems X” and the project Opportunity for young researchers, reg. no. CZ.1.07/2.3.00/30.0016, supported by Operational Programme Education for Competitiveness and co-financed by the European Social Fund and the state budget of the Czech Republic.

## References

[1] Atoui H, Fayn J, Rubel P. A Novel Neural-Network Model for Deriving Standard 12-Lead ECGs From Serial Three-Lead ECGs: Application to Self-Care," Information Technology in Biomedicine*, IEEE Transactions on* , vol.14, no.3, pp.883-890, May 2010.

[2] Rubel P, Fayn J. Quantitative assessment of eight different methods for synthesizing frank VCGs from simultaneously recorded standard ECG leads. *Journal of Electrocardiology*. 1991, vol. 24, s. 197-202.

[3] Bousseljot R, Kreiseler D, Schnabel, A. Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet. Biomedizinische Technik, Band 40, Ergänzungsband 1 (1995) S 317.

[4] Edenbrandt L, Pahlm O. Vectorcardiogram synthesized from a 12-lead ECG: Superiority of the inverse Dower matrix. *Journal of Electrocardiology*. 1988, vol. 21, issue 4, s. 361-367. DOI: 10.1016/0022-0736(88)90113-6.

[5] Kors JA, Van Herpen G, Sittig AG, Van Bemmel JH. Reconstruction of the Frank vectorcardiogram from standard electrocardiographic leads: diagnostic comparison of different methods *Eur Heart J* (1990) 11 (12): 1083-1092.