Intelligent Modeling of the Electrical Activity of the Human Heart

Lambros V. Skarlas, Grigorios N. Beligiannis, Efstratios F. Georgopoulos and Adam V. Adamopoulos

***Abstract*—**The aim of this contribution is to present a new approach in modeling the electrical activity of the human heart. A recurrent artificial neural network is being used in order to exhibit a subset of the dynamics of the electrical behavior of the human heart. The proposed model can also be used, when integrated, as a diagnostic tool of the human heart system.

What makes this approach unique is the fact that every model is being developed from physiological measurements of an individual. This kind of approach is very difficult to apply successfully in many modeling problems, because of the complexity and entropy of the free variables describing the complex system. Differences between the modeled variables and the variables of an individual, measured at specific moments, can be used for diagnostic purposes. The sensor fusion used in order to optimize the utilization of biomedical sensors is another point that this paper focuses on. Sensor fusion has been known for its advantages in applications such as control and diagnostics of mechanical and chemical processes.

***Keywords*—**Artificial Neural Networks, Diagnostic System, Health Condition Modeling Tool, Heart Diagnostics Model, Heart Electricity Model.

I. INTRODUCTION

THE definition of a model, in general, is to imitate an original system in order to give the best possible results or outcomes as the prototype system in the same, or nearly the same way. In our case, a model of an individual's heart system must present physiological measurements of variables such as the electrical potential of the human torso, the heart rate, the systolic blood pressure and the diastolic blood pressure for any person. This generalization of course, cannot lead to accurate and trustworthy results concerning people's medical condition.

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A model becomes personalised when it is being adapted to an individual. Then, it becomes a personal model concerning only that individual. This can be very useful for the medical treatment of that individual in later stages of his/her life. This personalised model for a healthy individual can be compared at any time to the actual measurements of that individual at a later time. Any variations found in new measurements can be exploited to evaluate and diagnose medical conditions that affect the clinical condition of that individual. More specifically, as far as heart models is concerned, the more measurements of older and more recent ECGs (ElectroCardioGrams) [1], [2] of an individual are compared, the greater is the percentage of correctly diagnosing future medical conditions concerning the human heart system. These models will also increase the sensitivity of detecting or excluding several other conditions that cannot be uniquely diagnosed in a test alone [3].

A model simulating the electrical activity of the heart can be easily incorporated into an automatic, continuous diagnostic system carried on a person. Physiological variables received from non-invasive biomedical sensors (such as the electrodes of an ECG test) can be compared with the modeled variables in real-time. In this way, an early, crucial and in real-time diagnosis of undesired medical conditions of an individual can be achieved. Also, the response time of medical help for people in immediate need, for example in car accidents, is reduced significantly. Reduction of the response time for delivering health care in severe situations, is very important. It helps minimizing medical complications and even loss of life. Another advantage of a real-time diagnostic system is the continuous monitoring of people with medical conditions in nursing homes and in home-care situations.

The technology used for the development of the human heart electricity model is the Artificial Neural Network (ANN) technology. ANNs [4], [5] have been widely applied to modeling complex process dynamics for the manufacturing and chemical industries [6]–[10]. In order to develop the above model the following assumptions were made. Firstly, that the human heart system exhibits similar dynamics and secondly that the system could be modeled with ANNs, since this technology has been successfully used in a variety of medical diagnostic systems and applications [3], [11]–[14].

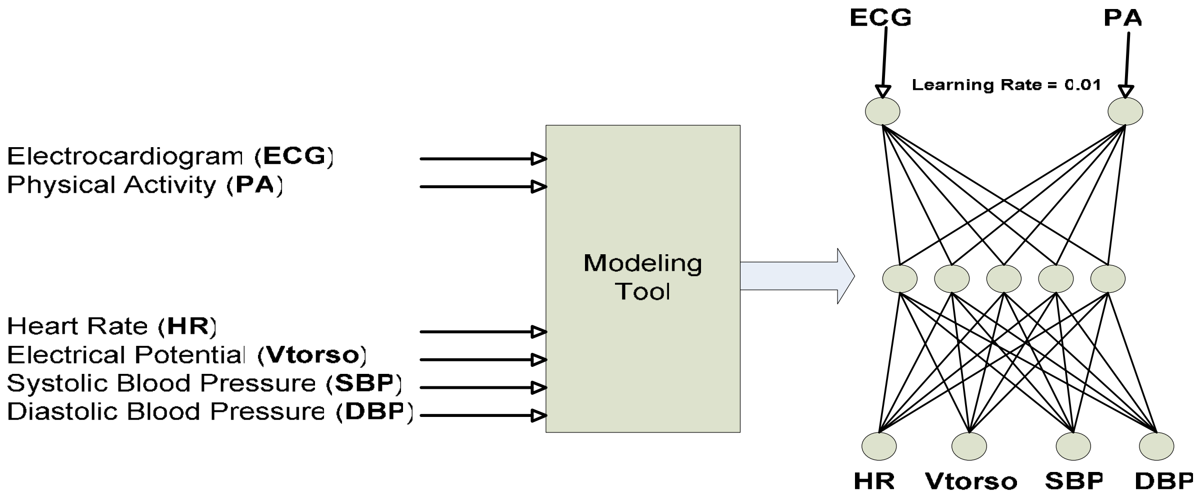

FIGURE 1
THE STRUCTURE OF THE MODELING TOOL USED TO CONSTRUCT THE ANN–BASED HEART ELECTRICITY MODEL

II. ANN BASED HEART ELECTRICITY MODEL

One approach to heart electricity modeling is to build a model representative of a group of individuals with similar characteristics (i.e., sex, age, physical and medical condition, etc.). However, human heart behaviour is unique to each individual [1], thus a generic heart electricity model used in a medical diagnostic system would not be as sensitive as a system based on a model that is adapted to the patient being diagnosed. To develop these models without a heart expert, the modeling must be based on an adaptive technology that can be automated. The ANN technology proves to be the most suitable type of technology used for this purpose. That is mainly because ANNs have been already used in many bioinformatics applications, especially for bio–signal analysis and prediction, and exhibited excellent results [15]–[19].

The use of sensor fusion enables the ANNs to learn complex relationships among the individual sensor values, which would otherwise be lost if the values were individually analyzed. In medical modeling and diagnosis, this implies that even though each sensor in a set may be sensitive only to a specific physiological variable, ANNs are capable of detecting complex medical conditions by fusing the data from the individual biomedical sensors.

The temporal information in physiological variables is captured by using recurrent ANNs which were selected for the heart modeling application. These variables are non linear time–series data (like the ECG measurements are time series recordings of the electrical activity of the human heart) from which both the absolute values and the monitored changes need to be modeled. Recurrent ANNs recycle a small portion of information from time t–1 at time t. Indirectly, decreasing portions of information from time t–i, for i=2,3,…,n, etc. are also captured, thus enabling recurrent ANNs to model the temporal dynamics contained in measured data. Fig. 1 illustrates a modeling tool that generates an ANN model of the heart electricity system from physiological variables received from biomedical sensors attached to an individual. On the left side, a modeling tool that takes a sequence of physiological variables from biomedical sensors and learns the temporal dynamics of these variables to produce an ANN based heart electricity model, is illustrated. On the right side, Fig. 1 illustrates the configuration of the ANN produced by the modeling tool. The ANN has two inputs, four outputs, and five hidden processing elements. The ANN takes the ECG measurements and the physical activity as input. The four outputs, which correspond to the heart rate, the electrical potential at the human torso, the systolic blood pressure and the diastolic blood pressure, are clamped to the "actual" values during the training phase. For the initial human heart model prototypes, the "actual" values are generated by a non-adaptive human heart model. During the modeling phase, the ECG measurements and the physical activity are the inputs of the ANN while the output values estimated are considered to be the modeled variables. The feedback links going through the five processing elements on the right side of the ANN enable it to capture temporal information among the data.

During the adaptation phase, the training algorithm receives data from an individual via biomedical sensors and automatically develops the ANN-based heart model. After the development phase has been completed, the model can generate the appropriate physiological responses for simulations with varying levels of physical activity. Fig. 2 presents the variables modeled with the ANN based heart model, compared to the physiological variables generated with a non-adaptive heart model. This model has been used for creating data with sufficient complexity in order to develop the modeling tool. More precisely, in Fig. 2 the "actual" and the modeled heart rate as well as the "actual" and the modeled systolic blood pressure for varying physical activity levels, is depicted. The "actual" values of the variables presented are generated with a non–adaptive heart electricity model [1]. The vertical axis corresponds to the magnitude of these variables (normalized to one).

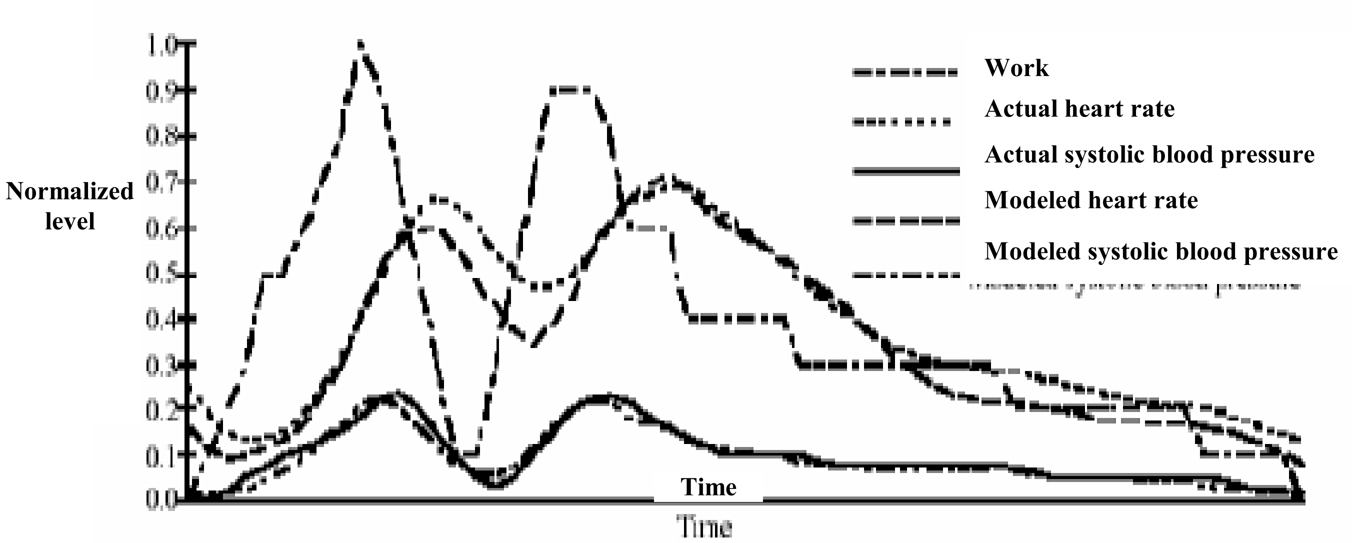

FIGURE 2
THE "ACTUAL" AND THE MODELED VALUES OF THE HEART RATE AND THE SYSTOLIC BLOOD PRESSURE FOR VARYING PHYSICAL ACTIVITY LEVELS

III. MODEL BASED HEART DIAGNOSTICS USING ANNS

It is envisioned that heart electricity models will be incorporated successfully in clinical diagnostic systems for tests, and especially in an automatic, continuous diagnostic system carried on a person. The methodology, for using models as a basis for diagnosis, is known as "model–based reasoning". Model–based reasoning compares actual data to modeled data, exploits the differences and uses the outcomes in diagnostic systems. In order this methodology to be successful, the models should be accurate to the systems being diagnosed and the differences between the modeled data and the actual data have to be known for diagnostic conditions.

Like mentioned before, conventional modeling techniques tend to build generic models with possibly a few free variables that fit the constructed model to a specific instance of a system. An ANN-based model is potentially a superior model because almost all of its free variables are adjustable to behave as a specific instance of a system. Conventional diagnostic techniques most often require that the differences between the modeled and actual data are known to the person developing the diagnostic system. These techniques are handicapped by both the ability of the person to understand the diagnostic differences in the data and by the applicability of those differences to the modeling technique. An ANN-based diagnostic system is potentially superior because it does not require a priori knowledge of the diagnostic differences in the data. However, it should be noticed that any useful knowledge will eventually assist the development of an accurate diagnostic system.

An individual's heart electricity behavior in normal conditions is used as a reference in a diagnostic system based on a specific model. Any variation from that behavior indicates a change from the normal condition. An ANN–based diagnostic system is able to recognize the effects of specific medical and physical changes on the monitored variables. For example, a blood loss results in decrease in blood pressure and an increase in heart rate relative to the normal values for that individual. Except for that, a sufficient measured time delay at the purkinje fibers [1], [2] has strong effects in the normal heart contraction. Fig. 3 illustrates the information flow within a heart diagnostic system that uses model–based reasoning to produce a diagnosis of the health condition of a specific individual. This is achieved by comparing a model constructed for the specific individual to the individual's current condition. The modeling tool receives the physiological variables from an individual via biomedical sensors. The diagnostic system receives the same variables from both the biosensors and the model. These two sets of variables are then "compared" in order to result in a diagnosis.

IV. DISCUSSION AND FUTURE WORK

The objective of this contribution is the presentation of a diagnostic tool which models a subset of an individual's heart system and uses model-based reasoning to determine the individual's health condition. Physiological measurements for an individual become the core of the modelling tool which learns the dynamics and the relationships between these measurements at different physical activity levels. The presented model is able to adapt to a specific individual and monitor his/her physical condition. As a result, it can be employed in uncertain medical scenarios to assist in the evaluation and immediate delivery of health care whenever medical and/or physical changes occur.

This diagnostic system aims to accomplish two major roles. Firstly, become a useful tool for health care practitioners, in the area of diagnosis. It can be used as a health diagnostic system either for continuous diagnosis of the clinical condition of patients or for periodic clinical tests. For example, ECG tests can be made without the need to visit hospital or primary health care centers. The latter is very useful in many countries where the National Health System suffers from

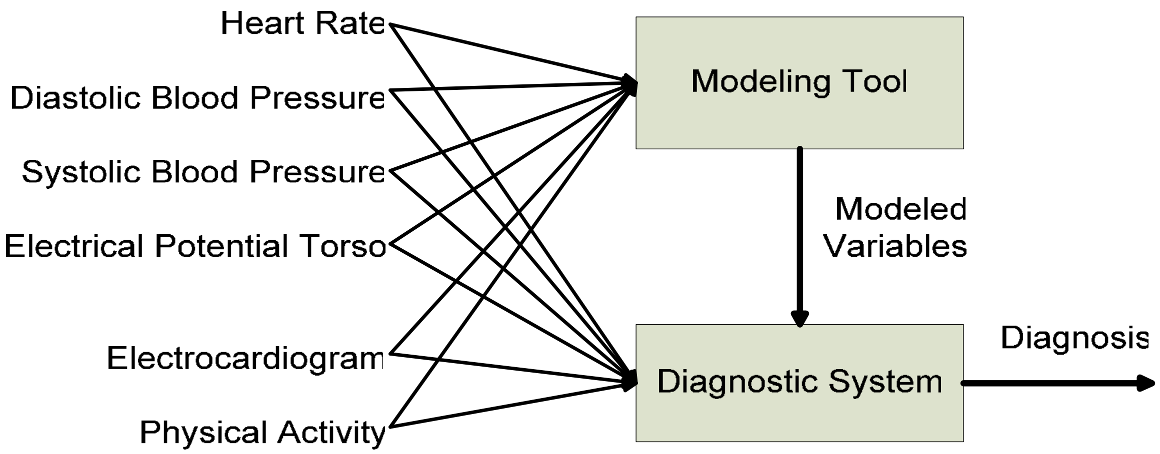

FIGURE 3
THE STRUCTURE OF THE HEART DIAGNOSTIC SYSTEM

organization inadequacy. Such a real–time diagnostic system using these heart electricity models may be used, for example, to monitor
the health of workers in hazardous environments or to monitor and control administration of medication for hospital patients.

Secondly, it can be used as a simulator for biological systems used in education and research related to human physiology.

It would be very interesting to investigate which of these biomedical sensors measurements can be compared with the modeled variables not only in real–time but also in an on–line diagnosis system. After the described heart electricity modeling tool is completed an advanced diagnostic system can be developed by integrating an ANN. Consisting of specialized clustering techniques and having the support of wireless communication systems will enable this diagnostic system to achieve data interchange concerning the medical history of each individual and essentially become an important on–line advice tool for every doctor. These issues will be the main scope of our future work.

REFERENCES

[1] J. Sundnes, G. Lines, P. Grøttum and A. Tveito, "Numerical methods and software for modeling the electrical activity of the heart", in *Computational Partial Differential Equations Using Diffpack - advanced topics*, H. P. Langtangen and A. Tveito, Eds. Springer LNCSE series, to be published.

[2] D. D. Di Bernardo, M. G. Signorini and S. Cerutti, "A model of two nonlinear coupled oscillators for the study of heartbeat dynamics", *Int. Journal of Bifurcation and Chaos*, Vol. 8, No. 10, 1998.

[3] D. Jones, "Neural Networks for Medical Diagnosis", in *Handbook of Neural Computing Applications*, Academic Press, 1990, pp. 309-318,

[4] S. Haykin, *Neural Networks: A Comprehensive Foundation*, Upper Saddle River, NJ. Prentice Hall PTR, 1994.

[5] H. White, "Learning in artificial neural networks: A statistical perspective", *Neural Computation*, Vol. 1, pp. 425–464, 1989.

[6] A. G. Parlos, K. T. Chong and A. F. Atiya, "Application of the recurrent multilayer perceptron in modeling complex process dynamics", *IEEE Trans. Neural Networks*, vol. 5, pp. 255–266, March 1994.

[7] M. H. Hassoun, "Neural Networks in Bioprocessing and Chemical Engineering", *IEEE Trans. Neural Networks*, vol. 7, pp. 1053, July 1996.

[8] P. J. Edwards, A. F. Murray, G. Papadopoulos, A. R. Wallace, J. Barnard and G. Smith, "The application of neural networks to the papermaking industry", *IEEE Trans. Neural Networks*, vol. 10, pp. 1456–1464, Nov. 1999.

[9] S. L. Ho, M. Xie, L. C. Tang, K. Xu, T. N. Goh, "Neural network modeling with confidence bounds: a case study on the solder paste deposition process", *IEEE Trans. Neural Networks*, vol. 24, pp. 323–332, Oct 2001.

[10] R. Gutierrez-Osuna and A. Gutierrez-Galvez, "Habituation in the KIII olfactory model with chemical sensor arrays", *IEEE Trans. Neural Networks*, vol. 14, pp. 1565–1568, Nov 2003.

[11] W. G. Baxt, "Use of an artificial neural network for data analysis in clinical decision-making: The diagnosis of acute coronary occlusion", *Neural Computation*, Vol. 2, pp. 480–489, 1991.

[12] B. Blumenfeld, "A Connectionist Approach to the Processing of Time Dependent Medical Parameters", in *Proc. of the 1990 Int. Joint Conf. on Neural Networks*, Washington, DC, Vol. 2, 1990, pp. 575-578.

[13] G. Dorffner, E. Leitgeb and H. Koller, "Toward Improving Exercise ECG for Detecting Ischemic Heart Disease with Recurrent and FeedForward Neural Nets", in *Neural Networks for Signal Processing*, vol. IV, J. Vlontzos, et al. Eds. Institute of Electrical and Electronics Engineers, Inc., New York, NY, 1994, pp. 499-508.

[14] R. L. Kennedy, R. F. Harrison, S. J. Marshall and C.A. Hardisty, "Analysis of clinical and electrocardiographic data from patients with acute chest pain using a neurocomputer", *Q J Med.*, Vol. 80, pp. 788-789, 1991.

[15] R. Silipo and C. Marchesi, Artificial Neural Networks for Automatic ECG Analysis, *IEEE Trans. Signal Processing*, vol. 46, pp. 1417–1425, 1998.

[16] A. V. Adamopoulos, E. F. Georgopoulos, S. D. Likothanassis and P. A. Anninos, "Forecasting the MagnetoEncephaloGram (MEG) of Epileptic Patients Using Genetically Optimized Neural Networks", in *Proc. GECCO-99*, Orlando, USA, July 14-17, 1999, pp. 1457–1462.

[17] K. I. Minami, H. Nakajima, and T. Toyoshima, "Real-time discrimination of ventricular tachycardia with Fourier-transform neural network", *IEEE Trans. Biomedical Engineering*, vol. 46, pp. 179-185, 1999.

[18] S. D. Likothanassis and E. F. Georgopoulos, "Self-organised evolutionary neural networks: algorithms and applications", in *Highly parallel computations: algorithms and applications*, WIT Press, 2001, pp. 397–433.

[19] Y. Hou, J. M. Zurada, and W. Karwowski, "Prediction of EMG Signals of Trunk Muscles in Manual Lifting Using a Neural Network Model", in *Proc. of the International Joint Conference on Neural Networks*, Budapest, Hungary, July 2004, pp. 1935-1940.