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P. E. Keller
L. J. Kangas
S. Hashem
R. T. Kouzes
P. A. Allen[a]

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Pacific Northwest Laboratory
Richland, Washington 99352

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A Novel Approach to Modeling and Diagnosing the Cardiovascular System

Paul E. Keller, Lars J. Kangas, Sherif Hashem, Richard T. Kouzes, and Paul A. Allen, MD*

Pacific Northwest Laboratory,† P.O. Box 999, K1-87, Richland, WA 99352, USA
pe_keller@pnl.gov, lj_kangas@pnl.gov

*Life Link, 949 Stevens Drive, Richland, WA 99352, USA

Abstract

In this paper, a novel approach to modeling and diagnosing the cardiovascular system is introduced. A model exhibits a subset of the dynamics of the cardiovascular behavior of an individual by using a recurrent artificial neural network. Potentially, a model will be incorporated into a cardiovascular diagnostic system.

This approach is unique in that each cardiovascular model is developed from physiological measurements of an individual. Any differences between the modeled variables and the variables of an individual at a given time are used for diagnosis. This approach also exploits sensor fusion to optimize the utilization of biomedical sensors. The advantage of sensor fusion has been demonstrated in applications including control and diagnostics of mechanical and chemical processes.

1. Introduction

A model of an individual's cardiovascular system must mimic the relationship among physiological variables (i.e., heart rate, systolic and diastolic blood pressures, and breathing rate) at different physical activity levels. If a model is adapted to an individual, then it becomes a model of the physical condition of that individual. A model for a healthy individual can be compared to the actual measurements of that individual at a later time. Any differences can be exploited to evaluate and diagnose medical conditions that affect the cardiovascular system of that individual. When used in clinical exercise testing (e.g., graded exercise tests), these cardiovascular models will increase the sensitivity of correctly diagnosing several medical conditions such as those listed in Table 1. These models will also increase the sensitivity of detecting or excluding several other conditions that cannot be uniquely diagnosed in an exercise test alone such as those listed in Table 2 [Jones 1988, Lamb 1984, Pollock 1990].

Table 1: Conditions detectable with exercise testing.

myocardial ischemia
peripheral vascular disease
exercise-induced asthma
vasoregulatory asthenia
unfitness
vasoregulatory asthenia
psychogenic dyspnea
muscle phosphorylase deficiency

Table 2: Conditions not directly detectable with exercise testing alone.

chronic bronchitis
pulmonary emphysema
pulmonary infiltration, alveolitis, and fibrosis
pulmonary thromboelism and hypertension
congenital cardiac abnormalities
cardiac valvular obstruction or incompetence
primary myocardial disease
generalized neuromuscular disorders

A cardiovascular model can be incorporated into an automatic, continuous diagnostic system carried on a person. Physiological variables received from noninvasive biomedical sensors can be compared with the modeled variables in real-time. This real-time diagnosis of an individual's general health increases the possibility of early detection of undesired medical conditions and reduces the response time of medical help for people working in hazardous and dangerous environments, (e.g., soldiers and law enforcement officers). A real-time diagnostic system also enables continuous monitoring of people with medical conditions in nursing homes and in home-care situations. Reduction of the response time for medical help is critical in minimizing medical complications and the loss of life.

Initially, we expect that employees working in hazardous environments would be monitored for early diagnoses of a degradation in health. The working environment and other causes may contribute to this degradation and make an employee unsuitable for certain work. For example, the described system could aid fire districts in determining the health effects from smoke inhalation on individual firemen. The system would determine whether firemen have recovered sufficiently from the last inhalations of smoke to be allowed to enter smoke-filled environments again.

The cardiovascular model is being developed with artificial neural network (ANN) technology. ANNs have been applied to modeling complex process dynamics for the manufacturing and chemical industries. We hypothesize that

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cardiovascular systems exhibit similar dynamics and can be modeled with ANNs. Additionally, ANN technology could be used to build the diagnostic system since they have already been successfully applied to a variety of medical diagnostic systems [Baxt 1991, Dorffner 1994, Jones 1990, Kennedy 1991, Mango 1994, Rosenberg 1994, Suzuki 1993].

2. ANN Based Cardiovascular Modeling

One approach to cardiovascular modeling is to build a model representative of a group of individuals with similar characteristics (i.e., sex, age, physical condition, medical condition, etc.). However, cardiovascular behavior is unique to each individual [Vander 1990], thus a generic cardiovascular 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 cardiovascular expert, the modeling must be based on an adaptive technology that can be automated. The ANN technology fits this category.

The ANN technology was selected for the cardiovascular modeling because of its many capabilities including sensor fusion, which is the combining of values from several different sensors. 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.

Recurrent ANNs were selected for the cardiovascular modeling application to capture the temporal information in physiological variables. These variables are time-series data from which both the absolute values and the rates of change 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-2, t-3, t-4, etc. are also captured, thus enabling recurrent ANNs to model the temporal dynamics in data. Figure 1 illustrates a prototype tool that generates an ANN model of the cardiovascular system from physiological variables received from biomedical sensors attached to an individual.

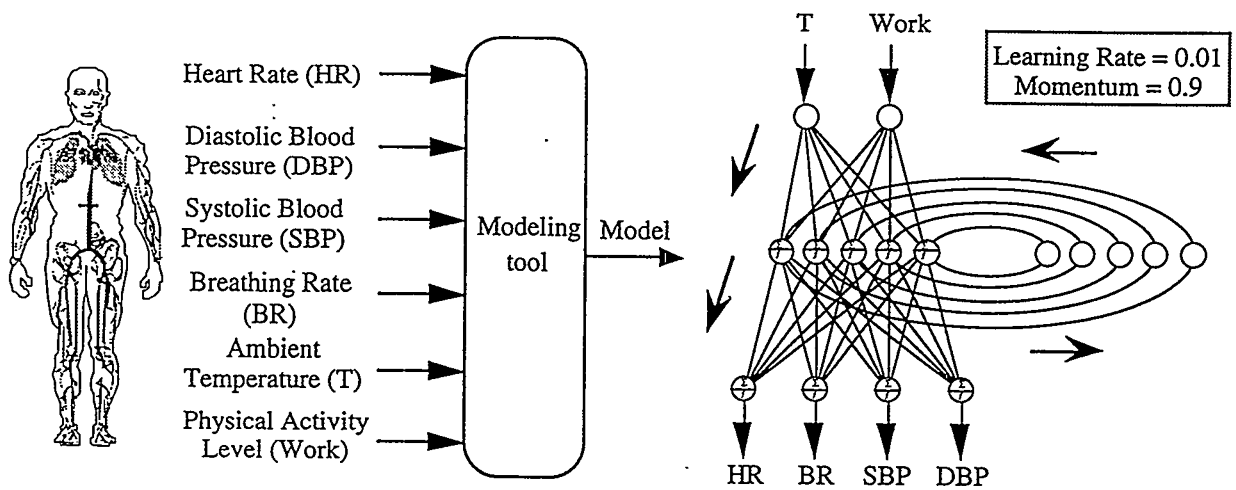

Figure 1. On the left, this figure illustrates a modeling tool that takes a sequence of physiological variables from biomedical sensors and learns the temporal dynamics of these variables to produce an ANN-based cardiovascular model. On the right, this figure illustrates the configuration of the ANN produced by the modeling tool. The ANN has two inputs, four outputs, and five hidden processing elements. The ANN takes the ambient temperature and the physical activity as input. The four outputs, heart rate, breathing rate, systolic blood pressure, and diastolic blood pressure, are clamped to the "actual" values during the training phase. For the initial cardiovascular model prototypes, the "actual" values are generated by a nonadaptive cardiovascular model. During the modeling phase, the temperature and the work are input to the ANN, and the values at the outputs are taken as 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 in the data.

During the adaptation phase, the training algorithm receives physiological data from an individual via biomedical sensors and automatically develops the ANN-based cardiovascular model. After development, the model can generate the appropriate physiological responses for simulations with varying levels of physical activity. Figure 2 shows how the variables modeled with the ANN compare with the physiological variables generated with a nonadaptive cardiovascular model. This second model has been used for creating data with sufficient complexity for the development of the modeling tool.

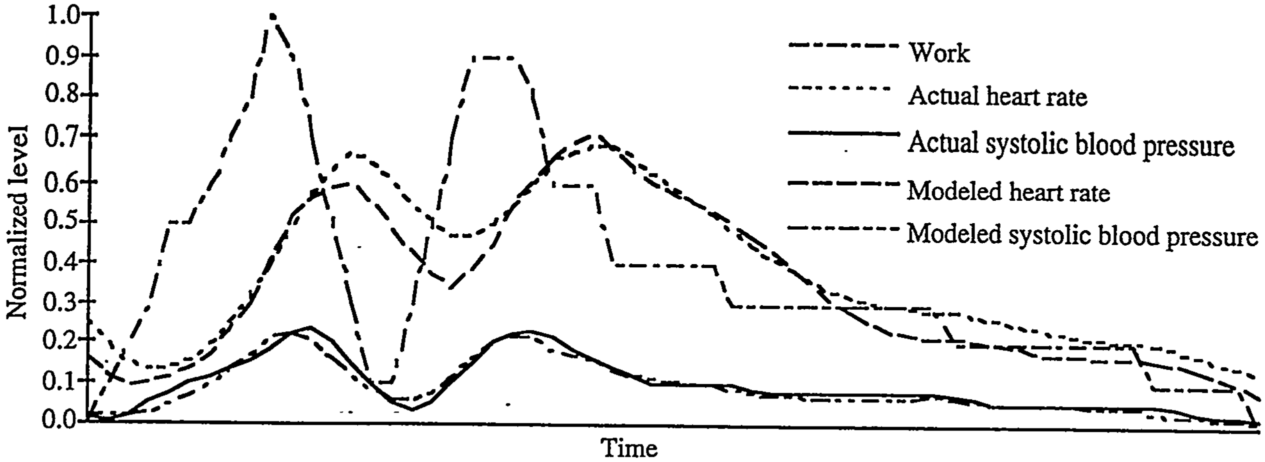

Figure 2. This graph depicts the "actual" and modeled heart rate, and the "actual" and modeled systolic blood pressure for varying physical activity levels. The "actual" variables in this graph are generated with a nonadaptive cardiovascular model. The vertical axis corresponds to the normalized magnitude of these variables (normalized to one). The variables for systolic blood pressure and breathing rate are excluded from this figure for clarity. The effects of varying ambient temperature has not yet been explored in this research.

3. Model Based Cardiovascular Diagnostics

It is envisioned that cardiovascular models will be incorporated in both clinical diagnostic systems for graded exercise tests and cardiovascular stress tests, and in an automatic, continuous diagnostic system carried on a person.

The methodology for using models as a basis for diagnosis is often referred to as "model-based reasoning." Diagnostic systems that use model-based reasoning compare actual data to modeled data and exploit the differences for diagnosis. Two prerequisites for this methodology to be successful are that the models are authentic to the systems being diagnosed and that the differences between the modeled data and the actual data are known for diagnostic conditions.

Conventional modeling techniques tend to build generic models with possibly a few free variables that fit the model to an instance of a system. For example, a respiratory system model-based on differential equations may have a few free variables adjusted to an individual's sex, age, and weight [Tehrani 1993]. 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, although it should be recognized that some knowledge aids the development.

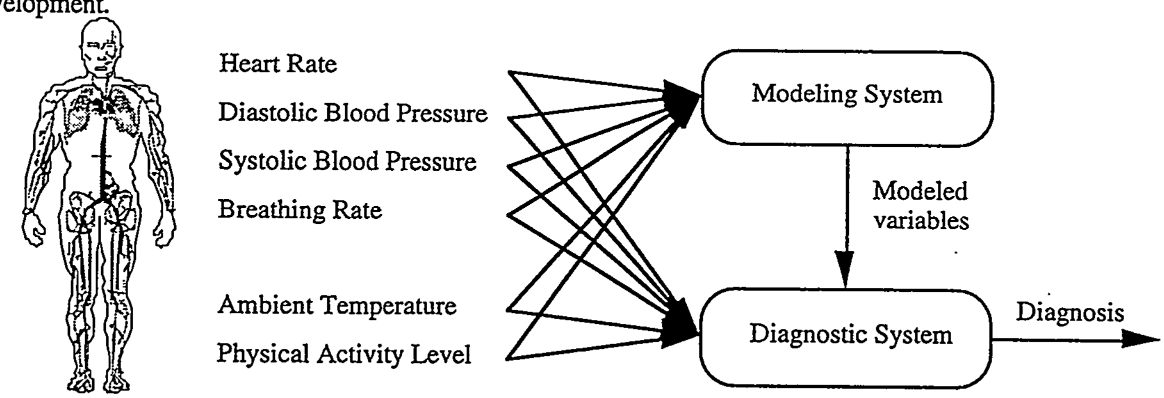

Figure 3. This figure illustrates the information flow within a cardiovascular diagnostic system that uses model-based reasoning to produce a diagnosis of health by comparing a model of an individual to the individual's current condition.

A diagnostic system based on a model uses an individual's normal-condition cardiovascular behavior as a reference. Any variation from that behavior indicates a change from the normal condition. An ANN-based diagnostic system is trained to recognize the effects of certain medical and physical changes on the monitored variables. For example, a blood loss results in a decrease in blood pressure and an increase in heart rate relative to the normal values for that individual. Figure 3 illustrates a diagnostic system and the information flow in model-based reasoning. 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 "compared" for diagnosis.

4. Discussion

This paper introduced a prototype diagnostic tool that models a subset of an individual's cardiovascular system and uses model-based reasoning to determine the individual's health. The modeling tool learns the dynamics of the relationship between physiological measurements for an individual observed at different physical activity levels. Because a model adapts to an individual, it duplicates the physical condition of that individual. As such, it can be employed in "what-if" medical scenarios to evaluate and diagnose medical and physical changes.

A tool of this type is envisioned to serve in two broad areas. First, it would serve in personal health diagnostic systems for continuous diagnosis of health and for periodic clinical tests: graded exercise tests and cardiovascular stress tests. For example, a real-time diagnostic system using these cardiovascular models may be used to monitor the health of workers in hazardous environments or to monitor and control administration of medication for hospital patients. Second, it can function as a simulator for biological systems used in education and research related to the human physiology and as a controller for medical mannequins.

In future work, this research will include the modeling of additional physiological variables, specifically variables describing pulmonary gas exchange: oxygen uptake (V_{O_2}), and the concentrations of carbon dioxide (CO_2) and nitrogen (N_2). A complete physiological exercise test should also include multichannel electrocardiography (ECG). After completion of the cardiovascular modeling tool, a model-based reasoning diagnostic system will be developed with ANNs.

Information on ANN developments at Pacific Northwest Laboratory is available in the World Wide Web (WWW) pages of the Environmental Molecular Sciences Laboratory. This information is accessible through WWW clients such as NCSA Mosaic. The uniform resource locator for this site is

`http://www.emsl.pnl.gov:2080/docs/cie/neural/.`

References

W.G. Baxt. 1991. "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.

B. Blumenfeld. 1990. "A Connectionist Approach to the Processing of Time Dependent Medical Parameters." *Proceeding of the 1990 International Joint Conference on Neural Networks*, Washington, DC, Vol. 2, pp. 575-578.

G. Dorffner, E. Leitgeb, H. Koller. 1994. "Toward Improving Exercise ECG for Detecting Ischemic Heart Disease with Recurrent and Feedforward Neural Nets." *Proceedings of the IEEE Workshop on Neural Networks in Signal Processing*, Ermioni, Greece.

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

N. Jones. 1988. *Clinical Exercise Testing*. W.B. Saunders Company, Philadelpia, 3nd edition.

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

D.R. Lamb. 1984. *Physiology of Exercise: Responses and Adaptations*. MacMillan Publishing Company, New York, 2nd edition.

L.J. Mango. 1994. "Computer-assisted cervical cancer screening using neural networks." *Cancer Letters*, Vol. 77, No. 2, pp. 155-162.

M.L. Pollock, J.H. Wilmore. 1990. *Exercise in Health and Disease: Evaluation and Prescription for Prevention and Rehabilitation*. W.B. Saunders Company, Philadelpia, 2nd edition.

C. Rosenberg, J. Erel, H. Atlan. 1993. "A Neural Network that Learns to Interpret Myocardial Planar Thallium Scintigrams." *Neural Computation*, Vol. 5, No. 3.

Y. Suzuki, Y. Abe, K. Ono. 1993. "Self-organizing QRS Wave Recognition System in ECG using ART2." *Proceedings of the World Congress on Neural Networks*, Portland, OR, 11-15 July 1993, Vol. 4, pp. 39-42.

F.T. Tehrani. 1993. "Mathematical Analysis and Computer Simulation of the Respiratory System in the Newborn Infant." *IEEE Transactions on Biomedical Engineering*, Vol. 40, No. 5, pp. 475-481.

A.J. Vander, J.H. Sherman, D.S. Luciano. 1990. *Human Physiology: The Mechanisms of Body Function*. McGraw-Hill Publishing Company, New York.