

Life Sign Decision Support Algorithms

C. Thomas Savell^a, Maurizio Borsotto^a, Jaques Reifman^{b,c}, Reed W. Hoyt^{b,d}

^a GCAS Inc., San Marcos, CA, USA

^b U.S. Army Medical Research and Materiel Command, Ft. Detrick, MD, USA

^c Telemedicine and Advanced Research Center, Natick, MA, USA

^d U.S. Army Research Institute of Environmental Medicine, Natick, MA, USA

Abstract

There is a pressing need in the military for a system that interprets data from a suite of wearable physiological sensors to infer a soldier's current clinical state on the battlefield. The Warfighter Physiology Status Monitoring (WPSM) concept is envisioned by the U.S. Army to address this need. Life sign detection is a key component. In the future the WPSM will consist of an array of biosensors embedded in the soldier's uniform all connected to a central processing control unit containing a computer chip with firmware for assessing the soldier's status. The unit will diagnose and transmit the Dead, Alive or Unknown physiological state to the field medic or elsewhere for status monitoring.

This paper describes the various modules that are found in the Dead/Alive determination algorithms and how they interact with each other, as well as a special simulator system built for use in parametric studies of the overall system. The current development of the firmware is described along with key requirements, outstanding challenges, and near and far-term research directions for the work.

Keywords:

Warfighter, Physiological models, Dead or Alive Assessment

Introduction

The U.S. Army Medical Research and Materiel Command is committed to developing methods for delivering the highest quality medical care to combat casualties on the battlefield. Many technological advances in medical monitoring have been made in the civilian sector, yet Army medics are basically equipped with tools almost unchanged during the last century. As a result, the mortality rate of wounded soldiers remains high and unchanged over the most recent conflicts. Often the first hour after injury is crucial. To stress this point, it has been reported that approximately 86 percent of all battlefield deaths occur within the first 30 minutes after the soldier is wounded [1]. Therefore the ability to rapidly locate, triage, diagnose, and render appropriate initial treatments are vital to improving the historical outcomes of battlefield injuries.

In response to this need the U. S. Army is developing a set of computerized devices as part of the Future Combat Systems initiative [2]. These devices will locate a wounded soldier quickly,

perform triage, monitor his/her vital signs and relevant physiologic information, and display their physiological status locally or remotely. The goal is to decrease mortality and morbidity to prevent disease and increase force effectiveness.

As part of this effort the Army is developing a **Warfighter Physiological Status Monitoring** (WPSM) system [2]. The system is intended to be a next-generation combat uniform featuring a configurable array of miniaturized sensors. The sensors will monitor heart rate, breathing, metabolic energy expended while working or marching, core skin temperature, activity patterns and several other parameters. These sensors will transmit their data to a central hub device so as to be stored, analyzed and, when desired, sent to command communication networks. To allow quick localization, the uniform will feature global positioning system capabilities. Life sign determination is one component of WPSM.

The various sensors are connected to a central processing control unit carried on the uniform. The processing unit is equipped with a computer chip containing firmware with a series of **Life Sign Decision Support** (LSDS) algorithms. The LSDS algorithms process the sensory information so as to produce meaningful information for combat medics and commanders. Specifically, as a first step, a **Dead, Alive or Unknown** (DAU) status is estimated by these algorithms and transmitted to the field medic or elsewhere as part of a larger soldier health monitoring system

Due to the critical application of these algorithms, a key requirement in their development is to reach a high level of confidence in the reliability of the DAU assessment. This means that the firmware must perform a statistical evaluation of the accuracy of the incoming signals as well as a probabilistic interpretation of the soldier's physiological state. As appropriate for the DAU application, these algorithms do not predict the future state of a wounded soldier but rather use present signal information and the associated uncertainties to determine the most likely current state of the soldier. The LSDS algorithms:

- Perform temporal analysis of the sensor data including the arbitration of contradictory information, processing different number of sensors, and performing non-monotonic reasoning on the collected data.

- Integrate elements of both clinical uncertainty and data imprecision derived from possible sensor / device faults and data transmission failure,
- Assess the reliability of the integrated circuit of sensors and devices by taking into account the probability of failure of each component as well as the probability of the failure of the integrated circuit and data transmission system as a whole, and
- Evaluate various sensor system configurations by indicating how the reliability of each component affects the reliability of the overall system.

The LSDS algorithms can identify sensor and transmission fault problems, including sensor dislodgment. Our simulator software can, among other things, be used to identify which measurements require redundant sensors, how many are needed, and the impact of such redundancy on the overall system reliability and accuracy. We can achieve these diverse features using the capabilities of the *Bayesian Network* (BN) statistical method in our algorithms [3]. BNs take into consideration both the reliability of the sensory information and the inference process associated with the human physiology model.

Software Architecture

The simplest way to understand the algorithms is to consider our prototype simulator software. The prototype is a diagnostic simulator of the *Human-Sensor-LSDS-Control-unit* combined system. It will produce data streams of simulated physiological parameters. These data streams will be useful in testing the diagnostic algorithms developed with the package. These algorithms, once implemented as firmware in the control unit, will have to run with data produced by actual sensors. In order to take into account the impact of the reliability of those real sensors, the simulator includes models encoding their behaviors. These sensor models perform two duties:

1. Sensor Reliability Determination in which the software package takes into account the sensor behavior for establishing the reliability of the diagnostic algorithms, (as well as computing an estimate of the reliability of a real hardware implementation as a whole and of every single component).
2. Real-time Simulation to model the behavior of an ideal “real” system.

Conceptually, the simulator represents a model of the WPSM hardware system during use by an individual, including a model of the individual himself as shown schematically in Figure 1. That is, we first model the hypothetical “true” physiological state of the human subject wearing the WPSM. This “true” state is represented by a composite group of individual physiological parameters such as heartbeat, oxygen saturation and brain activity. In the system, these data streams of physiological parameters are created by individual software modules called *Physiological Parameter Generators* (PPGs) that compose the *Human Simulator* on the left side of Figure 1.

Each PPG is devoted to a specific physiological parameter. The various PPGs are appropriately interconnected so as to create realistic and correlated data streams. The Human Simulator in

Figure 1 is actually a combination of the human and the array of worn sensors that distort the actual output from the human subject. This combination is necessary to achieve the goal of the Human Simulator to simulate “real” physiological parameters such as an actual human subject would produce.

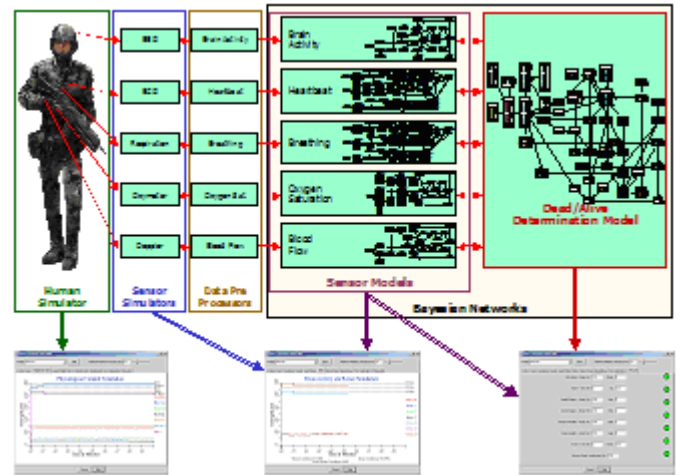


Figure 1 - General Architecture of the Software Simulator

These “real” physiological data streams will enter *Sensor Simulators* (SS) as shown in Figure 1. Each SS will model the behavior of a physical sensor intended to measure a physiological parameter. A SS is used to simulate the error and failure patterns of the sensor. These errors and failures “corrupt” the original data stream by introducing the idiosyncrasies of the sensor. For convenience, a SS also simulate the transmission system used for connecting the sensor to a central unit. Finally, a SS takes into account the self-diagnostic capabilities of the sensor. The output data from the SS simulates the real signal outputs from the array of biosensors worn by the soldier.

This “corrupted” data stream then enters the WPSM control unit and is processed by our firmware. Here, the data streams first enter a *Pre-Processor* (PrP). This component translates the data stream to quantities that fit the needs of the subsequent models. This is an interface between the sensory data and the diagnostic models.

Data leaving a PrP then enters a *Sensor Model* (SM). Here it is weighted according to its reliability, as determined from the characteristics of the sensor that “measured” the data. This weighting process is key for the goal of establishing the reliability of the system and of each single sensor.

The next step is to insert the weighted data into the *Dead/Alive Determination Model* (DADM). The DADM collects data coming from several sensors and performs a clinical diagnosis on a hypothetical human subject. The primary function of the DADM is to establish if the subject is dead or alive, but the capabilities of the DADM are not limited to this assessment and other important physiological observations are made related to the mental and physical health of the subject (such as the likelihood that the subject has lost consciousness), in order to provide an amber alert. (See Figure 4 later for a list of amber alerts).

The diagnostic outputs of a DADM then enter the *Post-Processor* (PoP), which is the last element in the chain. The PoP performs some final operations on the outputs and displays the results. In concert with SMs and DADM, the PoP: 1) Computes the reliability of the system and of each single sensor, 2) Establishes the capability of the algorithm to performing a satisfactory diagnosis, and 3) Computes the relative importance of the sensory sources for the diagnostic task.

Sensor Models & LSDS Algorithms

The various Sensor Models and Dead/Alive Determination Model were developed using Bayesian Networks. Bayesian Networks provide a method to represent interdependencies between propositions or variables, even if the relationships involve uncertainty, unpredictability or imprecision. The relationships may be learned automatically from data files, created by an expert, or developed by a combination of the two. BNs are used to develop knowledge-based applications in domains that are characterized by inherent uncertainty.

The basic idea in Bayesian Networks is that the problem domain is modeled as a set of nodes interconnected with arcs to form a directed acyclic graph. Each node represents a random variable, or uncertain quantity, which can take two or more possible values. The arcs signify the existence of direct influences between the linked variables, and the strength of each influence is quantified by a forward conditional probability. A typical Bayesian Network and some of its Conditional Probability Tables (CPTs) are shown in Figure 2. A CPT is used to define the probability (or likelihood) of the final state of a child variable based on the states of all the parent variables.

A BN allows us to combine prior knowledge and incoming data to the likelihood of a hypothesis of interest, such as a soldier being dead given his/her physiology and the sensory data time series.

The time dimension can be handled in a Bayesian Network by resorting to two strategies. The first one is to introduce explicit time variables, starting from the moment a specific condition or set of conditions occur. In our DADM network, a variable represents time elapsed since the heartbeat stopped. Another variable indicates when breathing has stopped. The second method handles time in an indirect way and leads to so-called “Dynamic BNs”. In this case, time is represented by discrete values. A model is created to represent the status of the world at a given time-slice. Time is implicitly represented by specifying how one set of variables at a given time-slice is affected by another set of variables at the preceding time-slice. While this is a more elegant approach, it has the drawback of slowing down the inference process. Care must be taken in order to balance cost and benefits. In our DADM model, the dynamics of oxygen saturation was modeled through this second technique. The DADM network is therefore making use of both the approaches described above.

The *Dead/Alive Determination Model* is a Bayesian Network used to infer the DAU status of a soldier from various sensory outcomes. The information used to construct the DADM model was gathered from literature [4, 5], legislation [6, 7, 8] and con-

sultation with Medical Doctors experienced in emergency room trauma situations. The DADM model also delivers a series of ancillary diagnostic conclusions that represent “amber” outcomes and warn about critical situations that may lead to a catastrophic event. For example, a low level of oxygen saturation triggers an alarm, as does the absence of breathing over a pre-defined period of time.

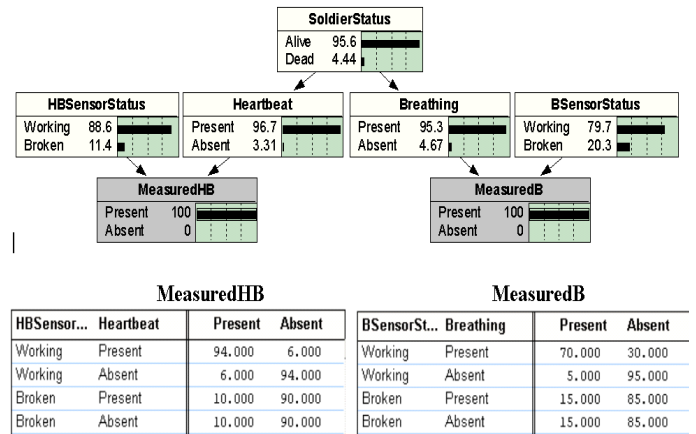


Figure 2 - Bayesian Network & Conditional Probability Table

DADM considers the following five physiological parameters: Heartbeat, Respiration, Brain Activity, Oxygen Saturation, and Blood Flow. The resulting DADM Bayesian Network encompasses 4,343 rules relating 45 variables. Although the overall model is very complex, it can be decomposed into fifteen individual *Elementary Models*, each dealing with a specific physiological issue.

In order to feed the DADM model with sensory data, we simulated a subject’s physical condition over a period of time. In this simulation we took into account different possible physiological behaviors as emerging from different individuals. This task is carried on by the Human and Sensor Simulators as discussed previously. Three basic profiles are encoded in our simulator representing individuals with different physical fitness. This, for example, affects the levels at which the heart rate is considered too fast or too slow, or the individual capability of coping with the lack of breathing.

The Human Simulator attempts to provide realistic physiological behavior during the dying process. It represents the assumed “true” physiology model inter-relating the time evolution of the five physiological parameters identified previously. Each simulated parameter features random fluctuations to provide realism and is individually created from a human profile. A central simulation manager contains a number of rules that link the various physiological states to provide realistic cause and effect patterns.

In the simulator, it is possible to associate up to three redundant sensors to each physiological parameter. The behavior of each sensor is modeled through an appropriate Sensor Simulator by superimposing to the physiological data a set of measurement errors and sensor/system failures, simulated for the following conditions:

- Small variance of the sensor reading,
- Incorrect sensor calibration,
- Improper positioning of the sensor,
- Dislocation of the sensor,
- Damage in the transmission system,
- Damaged sensor with stuck reading, and
- Broken sensor giving no signal.

In order to take into account the impact of the reliability of the sensors, we produced models encoding their behaviors. These *Sensor Models* were encoded with Bayesian Networks.

The variables for the Sensor Model BNs included: Sensor Intelligence in smart sensors, Sensor Failure Modes, Accuracy, Wearability, Redundancy, Electrical Integration Issues, and Data Transmission System and Protocols. Discussions with hardware experts enabled us to develop ideas to overcome the limitations of the various sensors through sensor redundancy and signal filtering.

The Sensor Models perform two duties. The first one is tied to reliability determination. In this mode the software package considers the sensors' behavior in establishing the reliability of the diagnostic output, thus computing an estimate of the reliability of a real hardware implementation as a whole and of its components.

The second duty is connected to simulation purposes. A real time simulation shows the expected behavior of a hypothetical physical prototype and helps the system developer to identify points of weakness and to devise, test and compare alternative solutions. Some examples are that an unreliable outcome caused by high levels of noise in a sensor translates into requirements for the sensor in terms of its accuracy and bias. Also, by trying different configurations, even with good sensors, the Dead/Alive Determination is not satisfactory (timely) if one uses only oxygen saturation. And third, several sensors sets and redundant sensors can be used in search of a satisfactory system behavior.

The data produced by the HPSS simulator are input into appropriate SMs before affecting the DADM model. In the SMs the data are weighted according to their reliability, as determined from the characteristics of the sensor that originated those data. This weighting process is important for the goal of establishing the reliability of the system and of each single sensor. A SM is also used in order to detect sensor failure from patterns of the data stream. Furthermore, it is useful for highlighting conflicts with data coming from other sensors related to the same or even different physiological parameters. This conflict detection feature is possible thanks to the intermediation of the DADM network. The DADM correlates the physiological parameters, thus generating an expected behavior for each one of them given the behaviors of the others. This expected behavior originates from the history of the performed measurements, the correlation between variables as expressed in the DADM, and the expected temporal evolution that the model itself entails.

The data streams produced by the Human Simulator and the SSs are displayed as individual time series as shown in Figure 3, where an athlete with an excellent level of fitness and cardiovas-

cular ability is modeled. During the first minute all physiological variables are left alone as the BN initializes. After 1 min 15 seconds the breathing was stopped. Around 3 minutes after breathing has stopped, the DADM automatically issued an alarm indicating a potential problem with the subject. Shortly thereafter the subject's status in the DADM model changes to "unknown" as oxygen saturation in the blood gets dangerously low. After 6-minutes of not breathing the subject status indicated death has occurred.

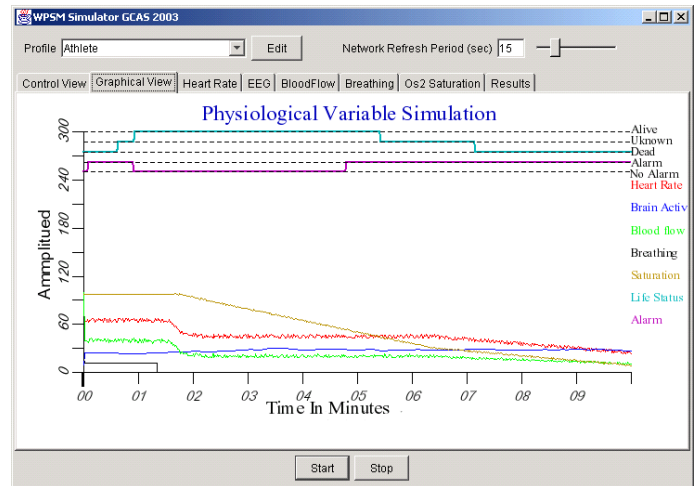


Figure 3 - Sensor Model Output

Figure 4 is the final output screen from the simulator showing circles on the right of each of the physiological parameters that change color from green to yellow to red, depending on the relative "goodness" of the related parameter. All of the parameters besides "Life Status" are examples of the kinds of "amber" alerts that LSDS can provide.

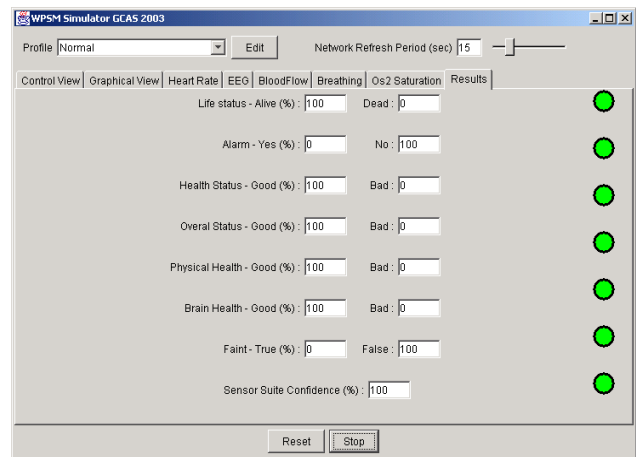


Figure 4 - Final Output Display

Conclusions and Future Work

This paper describes the first 6-month feasibility study phase of a 2-1/2 year effort to develop a Dead/Alive determination model for the Warfighter Physiological Status Monitoring system. The feasibility study included the definition of a set of LSDS algo-

rithms for determining the alive/dead status of a soldier, methods for performing probabilistic risk assessment analysis of a suite of sensor to be worn by the soldier, a set of sensor models used to detect sensor failure and condition the measurements according to the sensor's reliability, and the development of a prototype human physiology and sensor simulator for modeling and validating the combined human subject-sensors-WPSM-processor-control-unit system. The software simulator demonstrated the validity of the pursued approach.

Leveraging the results of our initial LSDS algorithmic formulation, we are now generalizing the system architecture and moving to the next phase. In this second phase we will create a user-friendly development platform using a flexible, "plug-and-play" framework for rapidly synthesizing and prototyping diagnostic algorithms for clinical conditions. Its main features will be easy scalability and modularity, so that a physiologist will be able to select and compose the diagnostic system through a simple interface. This is done by simply selecting a pool of sensors, placing them on appropriate locations on the human body and performing a set of simulations. The software will assemble the algorithms for the simulation model in the background, given the description of the sensors used, their characteristics and possible redundancy, their location on the body, etc. The developed BN sensor models will have a generic format to allow new, yet unknown sensors to be added with a simple user interface.

The user will be able to exploit state-of-the-art physiological simulators and data collected on the field and stored in a file or even use real time data streams. Indeed, in order to validate the final product we intend to use real measurements of humans and/or animals. This will allow the LSDS algorithms to diagnose the outcome that was experienced by the subject in real life. The resulting diagnosis from the model will then be compared to the actually achieved outcome.

Acknowledgement

The work described in this paper was funded by US Army SBIR contract DAMD17-03-C-0046.

Disclaimers

The opinions and assertions expressed in this paper are those of the authors and do not necessarily express the official views of the Department of the Army." "Approved for public release; distribution is unlimited."

References

- [1] CCCRP – Combat Casualty Care Research Program – U.S. Army Medical Research and Materiel Command (<http://www.usacc.org/aboutccc.jsp>).
- [2] Hoyt, R.W., Reifman, J., Coster, T.S., and Buller, M.J., "Combat Medical Informatics: Present and Future". In *Proceedings of the AMIA 2002 Annual Symposium*, pp. 335-9, San Antonio, TX, November 9-13, 2002.
- [3] Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems*, Morgan Kaufmann Publishers, San Francisco, CA, 1988.

- [4] Severinghaus, J. W., "Simple, accurate equations for human blood O₂ dissociation computations." *Journal of Applied Physiology*. 46(3): 599-602. 1979.
- [5] Lindholm, P., *Severe Hypoxemia During Apnea in Humans: Influence of Cardiovascular Responses*, Department of Physiology and Pharmacology Section of Environmental Physiology, Karolinska Institutet, Stockholm, Sweden, 2002.
- [6] *Uniform Determination of Death Act* (<http://www.law.upenn.edu/bll/ulc/fnact99/1980s/udda80.pdf>), 1980.
- [7] *Voluntary Consensus Guidelines For Determination of Death*. New York State Department of Health, 2003. (<http://www.health.state.ny.us/nysdoh/bsd/guidelin.htm>),
- [8] *Guidelines For Determination of Death by Irreversible Cessation of All Functions of the Entire Brain, Including the Brain Stem (Age Greater Than One Year)*. New York State Department of Health, 2003, (<http://www.health.state.ny.us/nysdoh/bsd/attach.htm>),

Address for correspondence

Mr. Maurizio Borsotto,

GCAS Inc., 1531 Grand Avenue, Suite A, San Marcos, CA 92069, USA, Phone: 1-(760) 591-4227, Fax: 1-(760) 471-9538,

Email: mborsotto@gcas.net

