AGENT BASED CASUALTY CARE – A MEDICAL EXPERT SYSTEM FOR MODERN TRIAGE

S.M. Wendelken[1], S.P. McGrath[†1] and G. T. Blike[2]

[1]Dartmouth College/Biomedical Engineering, Hanover, NH, USA

[†] Principal Investigator. Susan.P.McGrath@Dartmouth.edu

[2]Dartmouth Hitchcock Medical Center/Anesthesiology, Hanover, NH, USA

Abstract- **Ascertaining physiological state of soldiers deployed in the battlefield is essential for medical and strategic decision making. The diagnostic and treatment methods used in the battlefield are currently sub-optimal due to limited field resources and communication mechanisms. The system described herein is is designed to assess the medical status of deployed soldiers in near real-time in a way that will equal or surpass assessments performed by medics. In addition, this system can organize and distribute status information to appropriate members of the unit and up the chain of command to facilitate critical decision-making. Key among the components of this combat casualty care system are algorithms that assess physiological state. This paper discusses the development and evaluation of two different medical assessment algorithms .**

I. INTRODUCTION

Military battlefield scenarios have changed dramatically over the past century from casualty intensive trench warfare to covert, small unit operations. The health and safety of each individual soldier is now essential to the success of every mission. As a result, the care of wounded soldiers in the battlefield is becoming an increasingly important part of military operations.

The extreme conditions of combat make effective casualty care exceedingly difficult and put medics at great risk. Current combat care is sub-optimal due to limited communication and resources in the field. These circumstances lead to diminished casualty care and increased risk to the medic. A flexible and efficient communication system that allows for seamless exchange of information regarding a soldier's history, medical status, and treatment among all levels of combat care is essential for modern triage.

In other combat casualty care research efforts [3] the primary focus has been on the development of sensors and diagnostic equipment. While such advancements will improve combat casualty care at the individual level, they do not allow for the expedient exchange of information that is necessary to provide efficient combat casualty care. The effort described herein, called Agent Based Casualty Care (ABC Care) combines networking and sensor technology in a system that addresses these communication issues and automates the diagnostic, treatment, and triage tasks performed by medics.

ABC Care incorporates individual computing devices (either wearables or PDAs), a mobile agent information management network, a sensor capable of collecting pertinent physiologic data, an assessment and alert system that analyzes sensor data, an ad hoc wireless routing system that transports and distributes data among computers in the network, and a user interface that allows field and command personnel to access a soldier's health status remotely as well as issue treatment protocols (Figure 1). Here we focus on the algorithms implemented to assess physiological state.

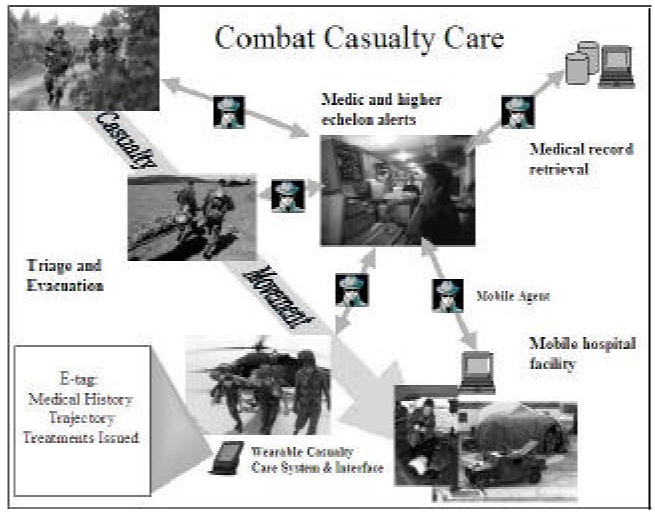

Figure 1: Agent Based Casualty Care scenario. A sensor collects physiological data that is analyzed and distributed using a wearable computer. During treatment and transportation of the injured soldier, the agent software continuously moves information regarding the soldiers' health up the chain of command appropriately.

II. METHODOLOGY

Since the 1970's there have been a number of rule based medical expert systems developed to assist medical diagnosis of diseases [4]. Combat care, however, has unique requirements due to the types of injuries sustained during combat and the restraints of limited resources in the field. There has been previous research in combat care and injury models [4,Bellamy] that we have incorporated into the design and implementation of ABC-Care.

We considered a number of modern artificial intelligence approaches in the development of our software including neural networks, fuzzy logic, and Bayesian probability theory. Ultimately, we decided to use a traditional rule-based system and fuzzy logic due to the practical drawbacks of implementing neural networks and Bayesian statistics [4, 1].

Our status assessment software incorporates an interactive medical model currently employed by medics and a rule base developed by a clinician. The algorithm uses these physiological parameters collected by a sensor worn by the soldier and the medical model to assess the soldier's medical status.

In developing the medical model, a simple but effective triage protocol designed by NATO was used [add reference]. This protocol prompts the medic to classify injured soldiers based on the location, type, and severity of the injury, as well as the soldier's cognitive and ambulatory state into one of several categories: Minimal (able to self-treat and walk to a casualty collection point); Delayed (able to self-treat but not able to walk); Immediate (serious injury requiring immediate treatment); and Expectant (serious injury with immanent death).

In the current ABC Care model, a soldier is classified into one of the four NATO triage categories if an event is detected and as 'normal' or 'unknown' otherwise. An event can be triggered in the following manners:

? The soldier self-triggers by pressing an icon on his or her touchscreen.
? The soldier's buddy (another soldier nearby) indicates that the soldier is down using his or her touchscreen and identifies the injured soldier.
? Physiological data lies outside the boundaries considered normal for soldiers in military action as determined by the status assessment software.

In this preliminary study, we used Matlab to develop the decision-making algorithms and to simulate data collection. With the help of an expert clinician, we simulated physiological data and interactive responses using the MILES (Multiple Integrated Laser Engagement System) combat casualty cards that are used to train medics. Because data collected from moving subjects is inherently noisy, we added noise to simulate motion artifacts in the data. Thus, we used a simple but effective limit-based artifact detection algorithm to smooth the data [2].

Because the physiological parameters vary significantly from soldier to soldier and the triage categories themselves are not crisp classifications, we tried two different approaches in structuring the status assessment algorithms. The first algorithm follows the exact rules and procedures defined in the medical model. The second incorporates the rules of the medical model into a fuzzy logic -based shell. Given data from a soldier and the rule base, this algorithm reaches a fuzzy classification of the soldier's medical status. The triage categories mentioned above were "fuzzified" along with many of the input parameters in order to simulate individual soldier vital sign variability and to incorporate system uncertainty.

Both algorithms use twenty-six input parameters describing the soldier's position, vital signs, ambulatory ability, and mental condition to assess the general medical status of the soldier. Vital signs, collected by a pulse oximeter sensor to be worn by the soldier include heart rate, perfusion index, and oxygen saturation. When the algorithm detects an event, it queries the soldier about his or her ambulatory ability, the location, type and severity of the injury, and his or her mental status (i.e. responsive, non-responsive, or deteriorating). The mental status is scored by a series of questions that the soldier must answer through the interface. In addition, the software can information provided by a buddy regarding the "ABCs" (Airway, Breathing, Circulation, and Shock) of the soldier in question. Using this information, the algorithms then classify the soldier's medical status.

The structure of both status assessment algorithms is a series of recursive functions. First, the main function obtains baseline measurements from the 26 input parameters. For subsequent time increments, this function checks equipment readiness and smoothes the data using an artifact detection sub-function. If the equipment is not ready then the algorithm classifies the soldier as Grey/Unknown. The artifact sub-function compares the current set of data with the previous set of data. If the difference between the current data and the previous data lies outside a given range, the sub-function determines a weighting factor based on the magnitude of the difference and computes a weighted average of the current and previous data. The new data is then replaced by the weighted average if the difference exceeded the given limits or left alone otherwise. The function then hands the new set of data back to the main function.

Next, the main function checks for buddy input and trigger criteria. If there is buddy input, the data is handed to another sub-function that classifies the soldier's health status based on the buddy input and then hands the data to a monitoring sub-function. If there is no buddy input, the main function for the hard-coded algorithm checks for any the following trigger criteria:

? Has the soldier self-triggered?
? Is the heart rate less than 40 bpm or greater than 200 bpm?
? Is the S_PO_2 less than 85%?
? Is the perfusion index less than 40% of the baseline measurement?

If none of these criteria are met, then the function classifies the soldier as White/Normal and hands the data back to itself. If any of these criteria have been met, the function begins to query the soldier and assess the status in the following way:

? Query 1: "Can you walk?" If the soldier answers 'yes' by touching an icon on the touchscreen[1] then the function classifies the soldier as Green/Minimal.
? If the soldier answers 'no' or does not answer within a specified amount of time, the function checks the S_PO_2.
    o If the S_PO_2 is absent, the function classifies the soldier as Black/Expectant.
    o If the S_PO_2 is low (less than 70% of the baseline measurement) then the function classifies the soldier as Red/Immediate.
    o If the S_PO_2 is adequate (greater than 70% of the baseline measurement) the function checks the heart rate and perfusion.

[1] We anticipate that future prototypes will use voice input for queries.

- o If the heart rate or perfusion is absent or low (heart rate < 40 or perfusion < 50% baseline), then the function classifies the soldier as Red/Immediate.
- o If the heart rate and perfusion is ok (heart rate > 40 and perfusion > 50% baseline) then the function checks the mental status of the soldier.
- o If the mental status score is acceptable then the soldier is classified as Yellow/Delayed. If the score is not acceptable or the soldier did not respond, the soldier is classified as Red/Immediate.

Following the classification, the main function hands the data to the monitor sub-function. This sub-function reads in the next time step of data and checks for buddy input and significant change in the vitals. If there is buddy input, this function hands the data to the buddy sub-function. Otherwise this sub-function smoothes the data using the artifact sub-function described above and checks if the current data point exceeds the running average of the data point by +/- 10%. If there is significant change, the sub-function hands the data back to the main function to be reclassified. If there is not significant change, this sub-function classifies the soldier with the same classification as the previous time step and hands the data back to itself. The main purpose of this sub-function is to avoid unnecessarily querying the soldier, thus distracting him or her from the urgency of combat situations.

The buddy sub-function uses the buddy input of the airway, breathing, circulation, shock, and level of consciousness of the down soldier to classify the medical status in the following manner:

- ? If the level of consciousness is 'unresponsive', then the soldier is classified as Black/Expectant.
- ? If any of the following criteria are met then the soldier is classified as Red/Immediate.
  - o Airway is partially or completely obstructed.
  - o Breathing is rapid and shallow or absent.
  - o Circulation: pulse can only be detected in the carotid artery or not at all.
  - o Shock symptoms are present.
  - o Level of consciousness: soldier is only responsive to pain stimu li or not at all.
- ? If the Airway is opened and the Breathing is normal and the Circulation is good and there are no shock symptoms present and the level of consciousness is optimal then the soldier is classified as Green/Minimal.
- ? Otherwise the soldier is classified as Yellow/Delayed.

The main purpose of the buddy sub-function is to take into account real-time expert data. The buddy sub-function overrides the status classification of all other functions.

The fuzzy algorithm shares the same structure of the hard-coded algorithm. The differences are in the assessment of a triggered event and classification in the main function. The fuzzy algorithm uses a fuzzy inference system to determine the possibility of a triggered event. Given a high possibility of an event, this algorithm uses another fuzzy inference system that uses the vital signs and responses to queries to classify the soldier using the following rules:

- ? If no trigger then status is White/Normal.
- ? If trigger and soldier can walk then status is Green/Minimal.
- ? If soldier cannot walk and S_PO_2 is 'low' then status is Red/Immediate.
- ? If soldier cannot walk and S_PO_2 is 'critical' then status is Black/Expectant
- ? If soldier cannot walk and S_PO_2 is adequate and heart rate or perfusion are 'low' then status is Red/Immediate.
- ? If soldier cannot walk and S_PO_2 is adequate and heart rate and perfusion are 'ok' and mental status is 'responsive' then status is Yellow/Delayed.
- ? If soldier cannot walk and S_PO_2 is adequate and heart rate and perfusion are adequate and mental status is 'un-responsive' then status is Red/Immediate.

The final status is given on a scale of 0-100, 0 being White/Normal and 100 being black/expectant. The classification number is calculated by the fuzzy inference system by the "center of mass" method.

III. Results

With the help of an expert clinician, we simulated the vital signs and other input parameters of 12 soldiers over 180 time increments. Both algorithms behaved as expected with 92% to 100% accuracy (explain). The hard-coded algorithm classified all soldiers correctly except for a soldier sustaining a blast injury resulting in hearing loss. In this case, the soldier was not able to provide data to the system. Without the soldier input, the algorithm classified the soldier two categories more severe than the soldier's actual status. The fuzzy algorithm performed marginally better but not significantly different (quantify). In the case of the soldier with hearing loss, the fuzzy algorithm classified the soldier only one category more severe than the actual status.

IV. Discussion

Because the fuzzy algorithm derives its rules from the hard-coded model, we expected both algorithms to behave similarly in this initial stage of prototype development. However, because the fuzzy system offers a higher resolution of classification and accounts for system uncertainty and physical variability among soldiers, we will anticipate using the fuzzy algorithm while using the hard-coded algorithm as a benchmark. Add something about what needs to be done next……

V. Conclusion

The initial results described above indicate that status assessment algorithms can be used to determine physiological state over a wide range of injuries. We believe that incorporation of such algorithms can improve combat triage by decreasing medic time spent performing event detection and diagnosis, thus allowing them to maximize their limited treatment resources.

ACKNOWLEDGMENT

This work was sponsored in part by the US Army's CECOM (Communications and Electronics Command) Division, Grant DAAB07-01-C-K218.

REFERENCES

[1] Binaghi, E. et al. Computers in Biomedical Research. Vol. 26, pp. 498-516, 1993.

[2] Cao, Cungen et al, Journal of Clinical Modelling and Computing. Vol. 15: pp. 369-378, 1999.

[3] Defence Advanced Research Project Agency (DARPA). Advanced BioMedical Technology Program.

[4] Hudson, D. and Cohen, M. Neural Networks and Artificial Intelligence for Biomedical Engineering. IEEE Press, New York. 2000. pp. 131-145.