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Adaptive Awareness for Personal and Small Group Decision Making

C. M. Pancerella, S. Tucker, A. B. Doser, R. Kyker, K. J. Perano, N. M. Berry

Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550

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Carmen M. Pancerella, Steve Tucker, Adele B. Doser, Ron Kyker,
Kenneth J. Perano, and Nina M. Berry

Sandia National Laboratories
P.O. Box 5800
Albuquerque, New Mexico 87185-9012

Abstract

Many situations call for the use of sensors monitoring physiological and environmental data. In order to use the large amounts of sensor data to affect decision making, we are coupling heterogeneous sensors with small, light-weight processors, other powerful computers, wireless communications, and embedded intelligent software. The result is an adaptive awareness and warning tool, which provides both situation awareness and personal awareness to individuals and teams. Central to this tool is a sensor-independent architecture, which combines both software agents and a reusable core software framework that manages the available hardware resources and provides services to the agents. Agents can recognize cues from the data, warn humans about situations, and act as decision-making aids. Within the agents, self-organizing maps (SOMs) are used to process physiological data in order to provide personal awareness. We have employed a novel clustering algorithm to train the SOM to discern individual body states and activities. This awareness tool has broad applicability to emergency teams, military squads, military medics, individual exercise and fitness monitoring, health monitoring for sick and elderly persons, and environmental monitoring in public places. This report discusses our hardware decisions, software framework, and a pilot awareness tool, which has been developed at Sandia National Laboratories.

This report describes work completed under Laboratory-Directed Research and Development (LDRD) Project 36828.

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Nomenclature

WPSM	Warfighter Physiological Status Monitor
RPD	Recognition-Primed Decision model
PAN	Personal Area Network
WLAN	Wireless Local Area Network
JESS	Java Expert System Shell
SOM	Self-Organizing Map

1. Introduction

Pervasive computing has been defined as "convenient access, through a new class of applications, to relevant information with the ability to easily take action on it when and where you need to." [1] Sensors, hand-held devices, and wireless communications provide the ability to monitor and access information from almost anywhere. By coupling different sets of sensors, secure wireless communications, and handheld computing devices with more powerful computers and intelligent algorithms, we can use sensor data to affect human decision making and provide awareness to individuals and teams.

At Sandia National Laboratories we are prototyping an adaptive awareness and decision-making tool, a combination of hardware and software that monitors a human's state and environment, uses knowledge about the human and potentially dangerous scenarios, and enhances the human's decision-making ability. This tool has broad applicability to emergency teams, military squads, military medics, individual exercise and fitness monitoring, health monitoring for the sick and elderly, and environmental monitoring in public places. Each of these applications requires the use of different types of sensors and application-specific software; yet common to all these applications is an integrated hardware-software infrastructure that can be adapted for individuals, situations, and applications. This infrastructure is sensor-independent and allows us to readily develop a new embedded system that is customizable for new sensors, an individual person, a new team, a changing situation, or a new application entirely.

The software framework is made up of generic, distributed agents that coordinate in order to deliver awareness to humans and a core toolkit of reusable software components which provide interfaces to the sensors and services to the agents. Agents reason across sensor and simulation data, and communicate with other agents on other processors.

In this report we discuss motivation for this work, present our approach, and describe a pilot system [2] that was developed and demonstrated at Sandia National Laboratories and promising results of our awareness algorithms. Our pilot awareness and warning tool is comprised of heterogeneous sensors; small light-weight, wearable processors; embedded intelligent software; and a wireless network connecting these processors with other computers.

2. Motivation

There are many applications that use sensors. Common uses include the monitoring of buildings and homes [3]; use of medical sensors for patient care [4] and aging population [5]; physiological status monitoring of soldiers [6]; and location sensors such as GPS. Though many of these projects involve the collection of large amounts of sensor data, the sensor data is not used to the fullest extent, that is to provide awareness to individuals and teams, to affect decision making of individuals and groups, and to provide knowledge in future situations.

Existing environmental sensors, location sensors, and health sensors provide an interesting collection of sensors that can be used by agents to recognize cues from sensor data and previous experience, warn humans of possible scenarios, and advise humans. The result is an awareness and decision-making tool that is useful to small teams entering a stressful and potentially dangerous situation in order to quickly assess and remedy a number of hazards. Our tool employs distributed sensing modules to gather sensor data and intelligent software agents to use this data and other knowledge in order to provide both personal awareness and situation awareness to humans during crisis situations.

In Figure 1, we show the use of our tool by a first responder team (fire fighters, bomb squad, or SWAT team). In this example, each responder in a small team is outfitted with various sensors, *e.g.*, chemical sensors, GPS sensors, and physiological sensors. The types of sensors can vary from responder to responder. The sensor data is collected and analyzed by an intelligent agent on a wearable personal processor. These personal processors are networked together with a group processor (*e.g.*, a laptop) in a secure, wireless network, and the resulting multi-agent system provides input to both individual responders, including a team leader, and the entire team while they respond to an emergency. On the group processor an agent can reason across the team, and provide a real-time assessment of each team member's condition and the health of the team, in plain terms and not in raw sensor data. Access to the group processor assists the leader in making a decision.

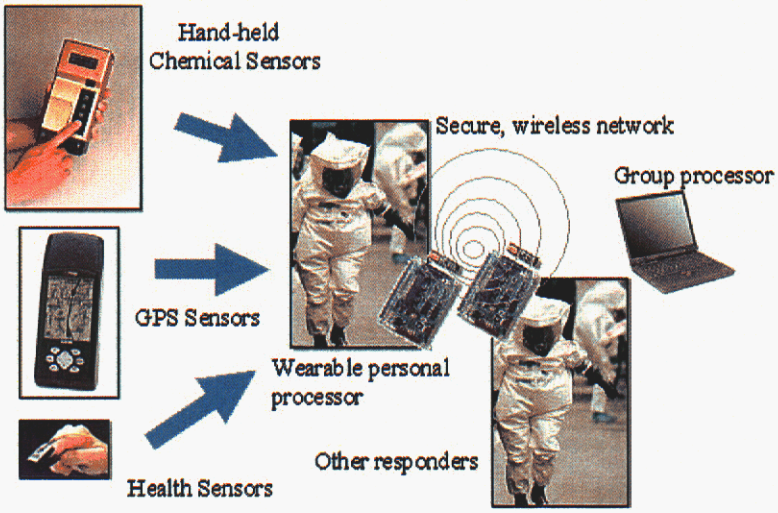

Figure 1. Applying the hardware system to a first responder application.

The Warfighter Physiological Status Monitor (WPSM) [6] is being developed to help field medics determine triage priorities. Additionally, a "smartshirt" [7], being developed at Georgia Tech, is designed to interface with sensors placed on the body. In both these projects, the research thrust has been on the development of mechanisms to collect and transmit the data, rather than the interpretation of the data collected. We are not aware of any related research projects to adaptively interpret the data colleted for each individual to identify his/her unique physiological state.

We are using physiological data as a measure of gross cognitive abilities to improve a team's decision-making and to improve an individual's understanding of his/her effectiveness/awareness. In wartime, soldiers have regular sleep deprivation and insufficient caloric intake and research shows that this has huge detrimental effects on soldiers' cognitive abilities [8], potentially eliminating effectiveness of our technology. First responders are typically well-rested and well-nourished. Hence, we believe that this tool initially is best suited to civilian or military first-responders instead of warfighters.

3. Awareness and Decision Making

A key challenge in the area of ubiquitous computing is the development of context-aware applications [9]. Context awareness is the "who's, what's where's, when's and why's of entities and the use of this information to determine why the situation is occurring. [10] We believe that this context awareness is especially of interest when individuals and/or teams are using sensors and handheld devices to recognize and assess personal and group situations. We are developing a tool to provide both situation and personal awareness to individuals and groups.

Endsley [11] has defined *situation awareness* as a human's perception of the elements within the environment, the comprehension of the elements' meaning, and the projection of their status in the future. Perception is an awareness; comprehension is the decision maker's holistic picture of the environment; and projection is the ability to predict future states. Research indicates that a person's situation awareness is the driving factor in the decision-making process. [12]

The recognition-primed decision model (RPD) [13] was formulated to explain how fire ground commanders use their expertise to identify and carry out actions without having to generate analyses of options for purposes of comparison. The RPD model has three functions: identify a situation with a simple match, diagnose the situation, and evaluate a course of action. One of the primary features in RPD is the ability to recognize critical cues. We are implementing the RPD model as a decision making aid: intelligent algorithms will recognize cues in complex sensor data and intelligent agents will compare these cues with previous knowledge in order to assist the human decision maker.

While situation awareness is useful to individuals and teams in recognizing potential problems, we contend that personal awareness is also of importance during decision making. Personal awareness is an individual's perception of his/her personal state, including his/her ability to make decisions. For example, fatigue, illness, and emotional stress all affect decision making, and a number of the symptoms of these adverse states can be detected by body worn sensors and knowledge about an individual. Note that some systems, *e.g.*, the WPSM, appear to provide personal awareness but instead only send personal sensor data to another computer or individual (often times a leader) or a team, and the individual does not benefit from the knowledge represented in the sensor data. We are advocating providing personal awareness to an individual so that he or she can use this information to make decisions. This same physiological sensor data can also be shared with team members in critical situations, and in this case, this is situation awareness. Hence, the same data is being used to provide both types of awareness and the intelligence in the system determine when this data needs to be shared with the entire team.

We believe that providing both situation awareness and personal awareness is valuable to individuals and teams and that coupling these two awareness levels is unique to our research. There appears to be little use of available **local** sensor data to improve **local** personal and situation awareness, despite the fact that the most pressing threats to the individual in an emergency situation are generally close at hand (within small arms range). Our work addresses this niche by providing the group leader, as well as individual team members, with the level of local awareness and team course of action decision support.

4. Approach

Rather than create a custom hardware and software package for each application, we are developing an integrated system that can be configured by developers of different applications. The system is constructed of commercial off-the-shelf hardware and common software platforms.

As seen in Figures 1 and 2, the flexible hardware infrastructure consists of sensors, small personal processors (*e.g.*, handheld devices), and larger group processors. One or more heterogeneous sensors are connected in a personal area network (PAN) with a personal processor. The PAN can be either wired or wireless. Desired features of the PAN include low power and short distance. The personal processors and group processors are wirelessly connected in a wireless local area network (WLAN). We expect that in most cases, a group processor is a laptop computer, personal computer, or workstation, though it may make sense for more powerful computers and other devices to be connected to the WLAN as well.

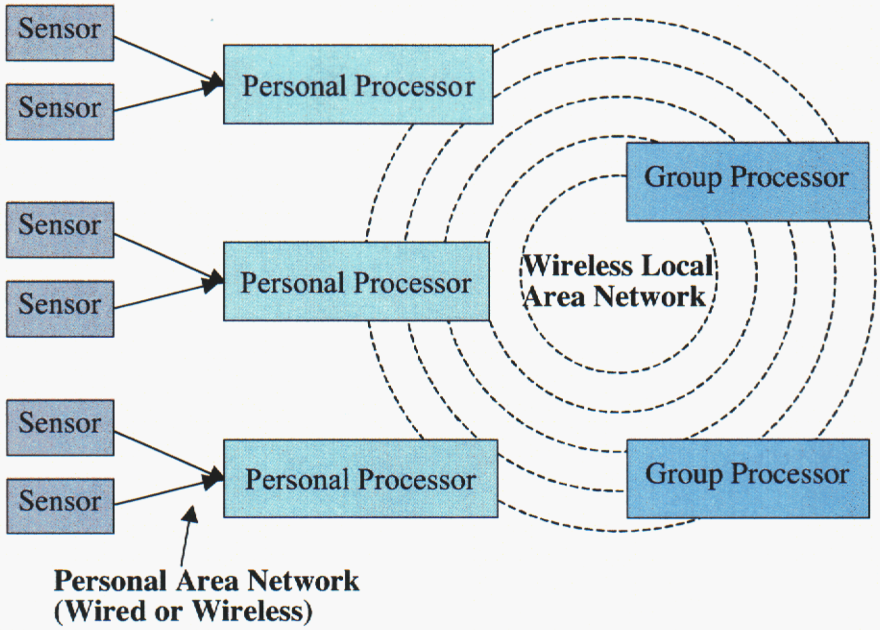

Figure 2. Integrated Hardware-Software System.

Although personal processors are typically smaller and less powerful than group processors, their power lies in the fact that as a group they are able to process and react to data from a set of sensors in parallel. As handheld devices become more powerful, this architecture becomes an impressive, albeit non-traditional, distributed computing cluster for mobile applications and pervasive computing. The personal processors and group processors can process large amounts of sensor data, execute complex intelligent algorithms, and collectively communicate using a wireless network.

There are a number of factors that must be considered in the selection of devices, PANs, and WLANs to support sensor-based applications. We list these factors here:

- Physical characteristics such as weight and size
- Power consumption
- Computing power and memory requirements

- Operating system availability and availability of sensor drivers
- Support for high-level languages
- Reliable network support
- Human factors, *e.g.*, available display features on personal processor
- Secure wireless PAN and WLAN, operating together

Some of these factors are more important in one application over another. For example, in a situation where the personal processors are worn by humans (*e.g.*, health and fitness monitoring), weight is likely more important than if the personal processors are stationary in a building (*e.g.*, environmental monitoring in public places).

With respect to high-level languages used in the development of software on personal processors, there are a number of issues to consider. In order to develop software agents and intelligent software components, it is necessary to use high-level languages. In particular, we are using C, C++, and Java, and our selection of processors and operating systems must support this decision. We have selected Linux as the operating system running on both personal processors and group processors. ANSI C allows us to write highly optimized driver code, which interfaces the sensors to the personal processors, and to develop intelligent data processing algorithms (*e.g.*, SOMs) used to pre-process and categorize the sensor data. We additionally use Java and Java-based tools on the group processors and personal processors for advanced sensor processing, reasoning, and communication.

The WLAN should provide secure, reliable connections that are extendable to connecting with PAN and traditional LAN. Reliable network support should have the following features: IP-based, device discovery, error handling/recovery, robustness, and scalability. While we are aware of the many concerns and inconsistencies surrounding wireless security within the wireless community [14], we have opted to use the current state of the art in 802.11b implementations at this time. This decision reflects our confidence in the wireless community to continue aggressive pursuit of improved solutions for this complex problem.

5. A General Software Framework

The software framework combines a reusable core of software components with software agents to implement the reasoning and coordination activities on the personal processors and group processors. The software core manages the available hardware resources, including the wireless networks, and provides supporting services for the agents. Agents, in the personal processors and the group processor, reason across sensor inputs, team members, and use previous knowledge to provide personal and situation awareness and to aid the decision makers. The software is designed to a handle a heterogeneous collection of sensors with minimal changes to the system. For example, in the first responder team application depicted in Figure 1, different responders may carry different types of sensors. This framework supports this by seamlessly integrating the sensors and other hardware devices and providing the ability to customize reasoning algorithms within the agents.

The software used to implement the general framework for the pilot project consists of the reusable software components that we have developed, integrated with tools for creating and customizing expert systems and self-organizing maps (SOMs), databases, and user interfaces. This software can be separated into three distinct levels, each consisting of several software components. The first level is the middleware used to capture the raw sensor data and the necessary interface(s) used to transfer the data to the personal processor device. We call the second level of the framework the personal processor software; this includes the application-specific sensor preprocessing with a software agent. An agent executing on the personal processor provides personal awareness and coordinates with other agents to provide situation awareness. The third level of the framework, known as the group processor software, consists of more complex agents which reason across collections of sensors, collectively provide situation awareness, and support higher-level decision-making. The reasoning ability of the agents on the personal processors is limited by the computing power, power consumption and memory of the personal processor itself. Therefore, in most cases, the more complex and resource intensive intelligent processing will be done at the group processor level.

To assist in the explanation of the software framework we will directly refer to a pilot implementation of a sensor-based awareness tool. The pilot project was designed to demonstrate scenarios consistent with first-responder, war-fighter, and military medic activities. While the hardware used in this pilot is discussed in detail in a later section, we introduce the hardware configuration to provide a basis for the software design. The hardware including sensors, personal processors (*i.e.*, Sharp Zaurus), and a group processor (*i.e.*, laptop), which correspond to the software levels discussed in the remainder of this section. The hardware used in our pilot exercise can be seen in Figure 3.

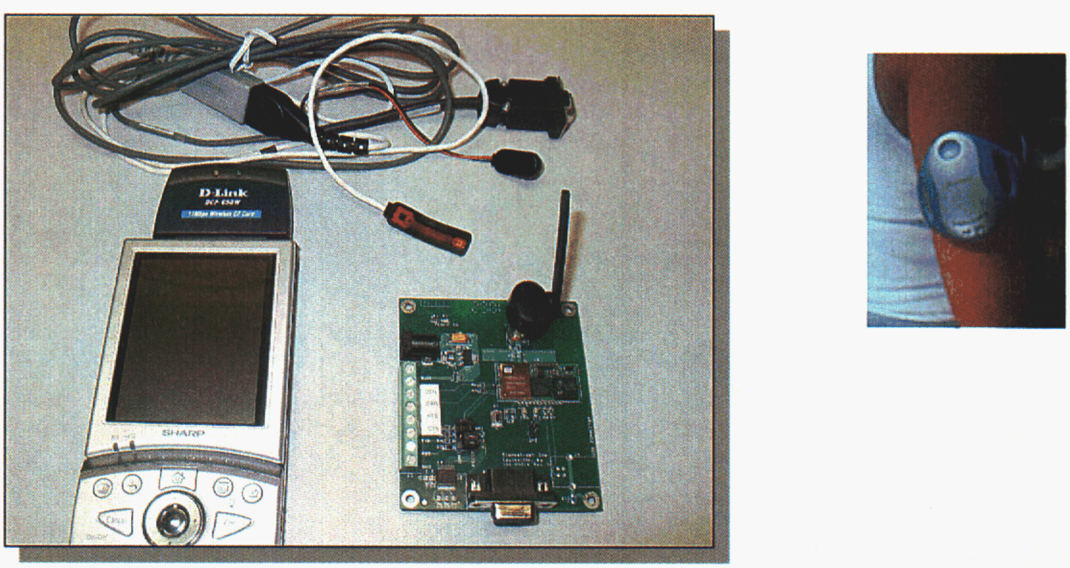

Figure 3. Demonstration System: Hardware setup and Body Media armband.

5.1 Level 1: Middleware to Interface Sensors with Personal Processors

The middleware used to interface the sensors with the intelligent agents on the personal processor is shown in Figure 4. This sensor component provides the hardware and software interfaces so that the intelligent agents, executing on the personal processor, can get the sensor data in an expected format. To the client program or intelligent agent executing on the personal processor, the sensor component provides methods which allow sensor data to be read and intelligent sensors to be configured, when possible. The API to this sensor component is general-purpose, supporting a wide range of sensors to be plugged into the back-end. We have tested this API with a number of heterogeneous sensors: GPS, pulse oximeter, and other physiological sensors.

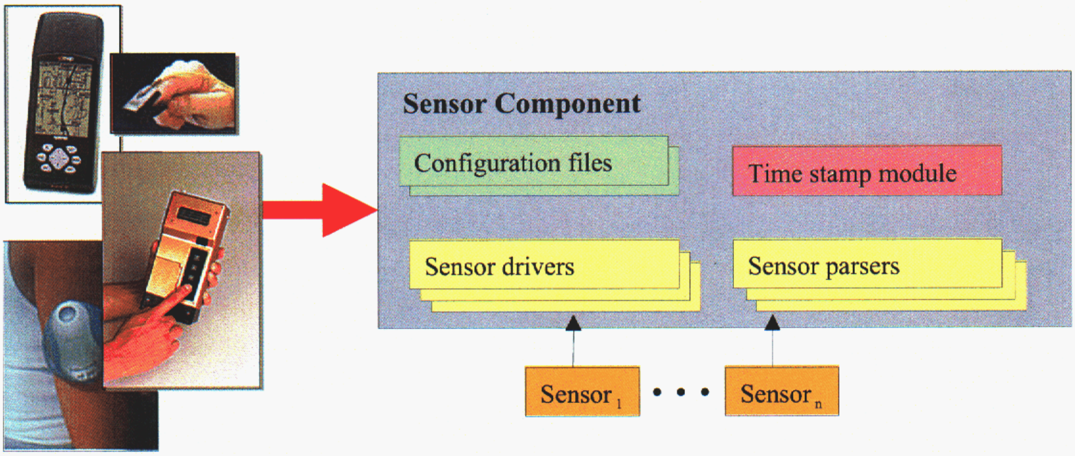

Figure 4. Middleware to interface sensors to personal processor software.

The sensor component encapsulates the sensor-specific driver programs and parsers. Typically an applications developer provides a sensor driver program and a unique parser for each sensor, and he/she creates or updates configuration files. The configuration files map specific sensors to both unique serial ports and sensor driver programs on the personal processor at run-time. As long as a driver program exists on the personal processor, the middleware does not have to be recompiled each time a new sensor is added, though configuration files will need to be modified.

A time stamp module ensures that multiple sensor inputs on a personal processor are synchronized to allow agents to reason about sensor inputs with a consistent clock. A unique parser for each sensor must be developed to convert the raw sensor data into an expected format.

5.2 Level 2: Personal Processor Software

The second level of the framework implements activities associated with filtering and/or preprocessing of the sensor data, as well as personal awareness. Personal processors are typically a small microprocessor device (*i.e.*, PDA) that could be held by a user; and the software at this level provides personal awareness and decision-making support to the individual user. As illustrated in Figure 5, the personal processor software includes software agents, data processors, filters, and reasoning algorithms to provide personal awareness and decision-making support to an individual and to provide situation awareness to the team.

The incorporation of software agents into the general framework is a robust and flexible way to achieve individual and team awareness and provide decision-making support. The agent module is controlled by an agent control unit, which acts as the "brains" of the agent. The control module decides how the internal software modules are executed and how parsed sensor data is initially processed. The knowledge base is where the agent stores knowledge about the individual person as well as the situation in order to provide personal awareness. The knowledge base on the personal processor agent is likely small due to the memory limitations of the personal processor. The agent reasoning algorithms are specific to an application or situation and are used in conjunction with the data processing, filters, and other agent input to enhance decision-making process.

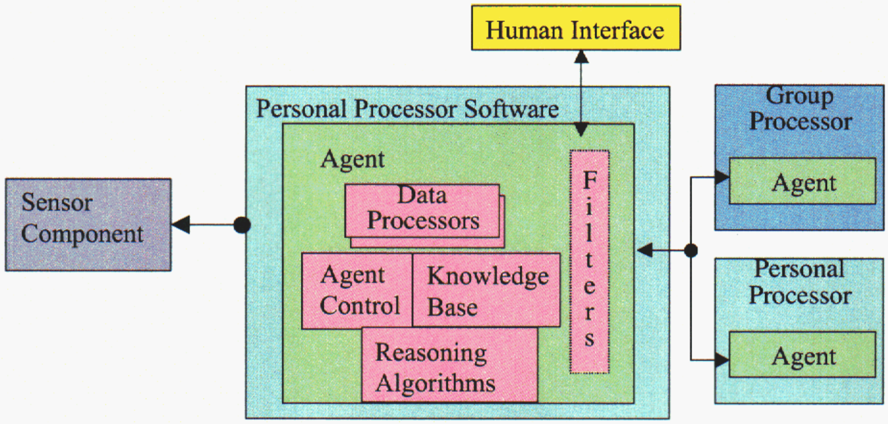

Figure 5. Personal Processor Software.

The data processors and filters allow sensor data to be processed locally, and certain events and cues can be ascertained from the intelligent processing of this data. Consequently, all sensor data will not have to be sent to the group processor for additional processing; this controls the amount of data that needs to be sent out on the WLAN. Agents determine which data needs to be sent to agents on other processors and what events need to be communicated with other agents. As shown in Figure 5, an agent executing on a personal processor can communicate in a peer-to-peer manner with either an agent executing on a group processor or other agents executing on personal processors.

The agent employs different intelligent data processors for one or more sensors in order to categorize the data and detect cues in the data. The intelligent algorithm used in the pilot project to process sensor data was a Self Organizing Map (SOM) [15]. The map was trained to recognize normal/abnormal sensor data for the individual wearing a Body Media SenseWear Armband [16]; this armband includes the following sensors: 2-axis accelerometer, heat flux, skin temperature, near body ambient temperature, galvanic skin response, and heart rate receiver. We selected this particular apparatus because these sensors provide the majority of data types required for physiological monitoring in a stressful environment [17].

The SOM was initially trained with real sensor data from all sensors (over 24 hours worth of training data) and labels were applied to the map after some initial training to depict the normal and abnormal data areas within the map. A SOM was created for each individual person. The advantage of using SOMs in the intelligent data processing components is the adaptability of the module to the individual user, since the SOM can be trained with an individual's physiological sensor data. Training of a SOM requires a large amount of physical data, and takes more memory and computing power than a typical personal processor. Hence, training was done on a more powerful computer, and the resulting SOM was then downloaded onto the personal processor. In the pilot project the SOMs used in conjunction with some individual knowledge about a particular user and the current situation provided personal awareness to that user. For example, if the personal processor agent knew when the user last slept and for how long he/she slept, it was able to suggest fatigue to the individual user based on this knowledge and the intelligent processing of the physiological data. We present specific physiological data in Sections 7 and 8.

A unique aspect of SOMs is that they can adapt over time with changing data. Hence, a personal processor can in effect learn about its user over time. We imagine outfitting a responder with such a personal awareness tool during his/her training exercises, and as the responder becomes more physically fit, that person's "normal" physiological state will also change. Of course, this learning has to be controlled so that the SOM does not "learn" about abnormal situations and not recognize them. A SOM, by itself, is an unsupervised training method, which simply creates a reduced dimensional mapping from an input to an undesignated output, without placing labels on the output. A SOM may be used in conjunction with a clustering algorithm, which organizes the map into regions and labels classes from similarities in the mapping. Yet here, too, in the classical implementation there is no input from the user, except perhaps to designate the number of classes. One result could be a clustering which produces many different classes representing situations of little interest (*i.e.*, there might be 3 classes related to the individual eating a meal, and only one class representing a host of activities of interest). Although it is possible that a combination SOM and clustering algorithm could produce a desired classification mapping on their own, it is much more certain this can be achieved with some intervention from the user/developer.

How, then, can a user influence an unsupervised training scheme? One solution would be to instead use a supervised clustering scheme, where a desired answer for every point is given. Such an approach would require the wearer of a device to keep a log of what he/she is doing at every minute of the day. This could be quite costly and would detract the wearer from his/her job. Another solution can be found by allowing the wearer of the device to be actively engaged in the training process, yet make this contribution as unencumbering as possible. Many off-the-shelf wearable sensors have a time stamp button, allowing the wearer to designate an activity of interest simply by pressing the button during the activity. The wearer can then make a note regarding the nature of each activity time stamped, rather than keeping a detailed log of all activities. Over the course of a day, the wearer may designate 6-12 unique activities. The SOM, as it is an unsupervised algorithm, is then trained without knowledge of these activities. However, when the map is clustered, the mapped locations of the activities of interest can be presented to the clustering algorithm. The clustering algorithm can keep adding dimensions until the desired activities can be represented in different classes. If a wearer designates two activities that are close together in feature space (*i.e.*, running up a staircase and running down a staircase), the clustering algorithm may need to add additional dimensions in order to classify these data as separate events. The result is that one may obtain more classes than the number of activities of interest that were designated via time stamp. These added classes represent other activities, such as eating, that the wearer may not designate. It is at the discretion of the developer to decide the relevance of these other classes, and whether or not to retain them or merge them with other activities. The result is a training method that allows the user to designate activities that are of importance to him/her, and to alert the developer to other activities that may be of importance. The training is done off-line and can be repeated as the situation changes. We have found this approach has proven useful in the classification of physiological data in non-critical situations [18].

The knowledge base for an individual user can become quite sophisticated over time; however, if the processing or memory requirements exceed current personal processor limitations, some of this knowledge might be transferred to a knowledge base on a group processor in the WLAN. Agents executing on personal processors and group processors can communicate this knowledge to each other. In this case, personal awareness is actually achieved with agents executing on both a personal processor and a group processor.

The agent uses the filters to regulate the flow of information to the other processors, typically to the group processors. The selection of the filters and the decision of how frequently information is transmitted to the other group/personal processors resides in the reasoning algorithm module.

When an agent receives new information from another agent, the reasoning algorithm evaluates this information. This new information can be combined with existing information and may be presented to the user through the user interface. On a PDA, the user interface is quite simple, with simple text and icons.

As we mentioned in this section, agents communicate as peers. In our pilot project, we used Java RMI to handle transmission of data between the different processors.

5.3 Level 3: Group Processor Software

The third level of the framework addresses issues of reasoning across collections of sensors and individuals and providing situation awareness and higher-level decision-making support. The group processor device is typically a laptop or PC device used by a team leader or a base installation. The major software modules of the group processor are illustrated in Figure 6 and include the software agent, knowledge base, data processors, reasoning algorithms, and database for archiving information.

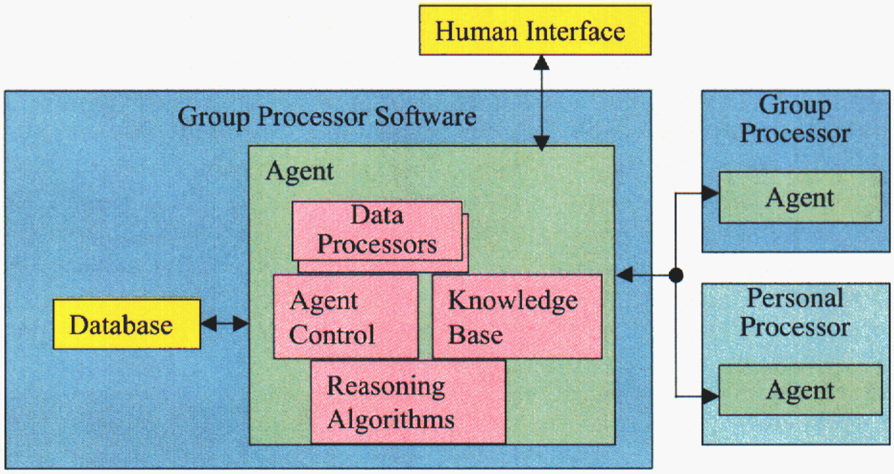

Figure 6. Group Processor Software.

The group processor contains one or more high-level reasoning agents. These agents can analyze patterns in data across many personal processors (*i.e.*, individuals), and use past data and simulations in order to recognize scenarios and cues. The structure of the software agent used in the personal and group processors are similar in their basic functionality; both use agent control and reasoning algorithm modules. The group processor agent is probably more sophisticated, however, because of the available memory and computing power on the group processor and also because the typical functions of a group processor agent are themselves more complex. Processing of multiple sensors across individuals and related data is handled by the data processor module, which itself could contain a neural network, SOM, or other intelligent algorithms used to refine the data. The knowledge base is used to store current and relevant information, for use by the agent control and reasoning algorithms, as well as other agents.

The reasoning algorithms integrate the sensor data with information from the knowledge base and knowledge from other agents. In the pilot project we used the Java Expert System Shell (JESS) [19] to provide an environment for reasoning about the sensor data from both the GPS and physiological sensors.

Our pilot exercise was simple in order to demonstrate the feasibility of the system. JESS was used to establish, maintain and combine multiple users' personal health (one sensor from the armband) and location information (GPS data) and to make decisions about the current situation of the team. The group processor received periodic data from two personal processors. Each personal processor agent reported pulse rate, personal awareness activity based on the SOM, and its location to a group processor agent. The group processor agent used combined sensor reasoning to recognize when a user's pulse was high and he/she was in motion versus when a user's pulse was high and he/she was stationary. The system could suggest that if the person was in motion that the high pulse rate was normal, whereas a high pulse rate with no motion may indicate a potentially stressful situation. The ability to classify pulse rates as normal or abnormal (high or low) was the result of the personal awareness and data processing provided by the SOM on the personal processor. The group processor can distinguish when more than one team member appears to be in movement, and may recognize a situation before individuals can report it to a team leader. The output of the reasoning on the group processor was then broadcast to both personal processors so that the team had situation awareness and team members could make decisions accordingly. It is useful for a team member to know when another team member might be fleeing (*i.e.*, in motion) or in a possibly stressful situation.

The agent can archive any data in its database for future retrieval and analysis. In our pilot project we developed a secure web interface to the database, which allowed a team leader to select and graphically display some critical sensor data from the personal processors. We also displayed the GPS data with MapQuest to display locations on a map. These interfaces provide a more useful interface to a leader, who cannot spend valuable time reviewing raw sensor data. We also provided alert messages when a potential medical situation arises, as the average team leader is not a medical professional.

Though our demonstration scenarios in the pilot project were simple, the framework allows for much more complex scenarios to be tested.

6. Pilot Project

We have built a pilot implementation of a sensor-based awareness tool, including sensors, two personal processors (two Sharp Zaurus handheld computers, as in Figure 3), and a group processor (a laptop). This particular handheld runs Linux natively, and has a full keypad, as well as Compact flash, USB, and IrDa ports. All computers are outfitted with 802.11b cards for wireless communications over TCP/IP at up to 11 Mbps. Typical range for our demonstration is 100 meters.

We have connected a Nonin Pulse Oximeter with a fingertip sensor to the personal processor; this sensor reports Oxygen saturation and pulse rate. We have also connected a Motorola GT Plus Oncore GPS Receiver. While the pulse oximeter is interesting, the Body Media SenseWear Armband, shown in Figure 3, provides a wider range of physiological sensors, and hence, more useful information. Therefore, we are exclusively using the Body Media armband to collect data in the pilot activities discussed below.

In our pilot, the sensors were not connected in a wireless personal area network (WPAN). We are currently developing a WPAN for each personal processor. Since it is our eventual goal to be capable of supporting a multitude of sensors, it becomes cumbersome to be able to physically connect several sensors into a personal processor in such a way that it is mechanically sound, comfortable, and without a mass of wires. The WPAN not only reduces the cabling but also provides a realistic and flexible model for deployment in the field, since the suite of sensors could be unique for each individual based on awareness goals.

7. Initial Results

We collected data from several human subjects, who wore the Body Media armband. In Figure 7, we see the raw data from one of the sensors, that is, skin temperature, for one particular subject. As you can imagine, the skin temperature is hottest during exercise. We used this data to train a SOM.

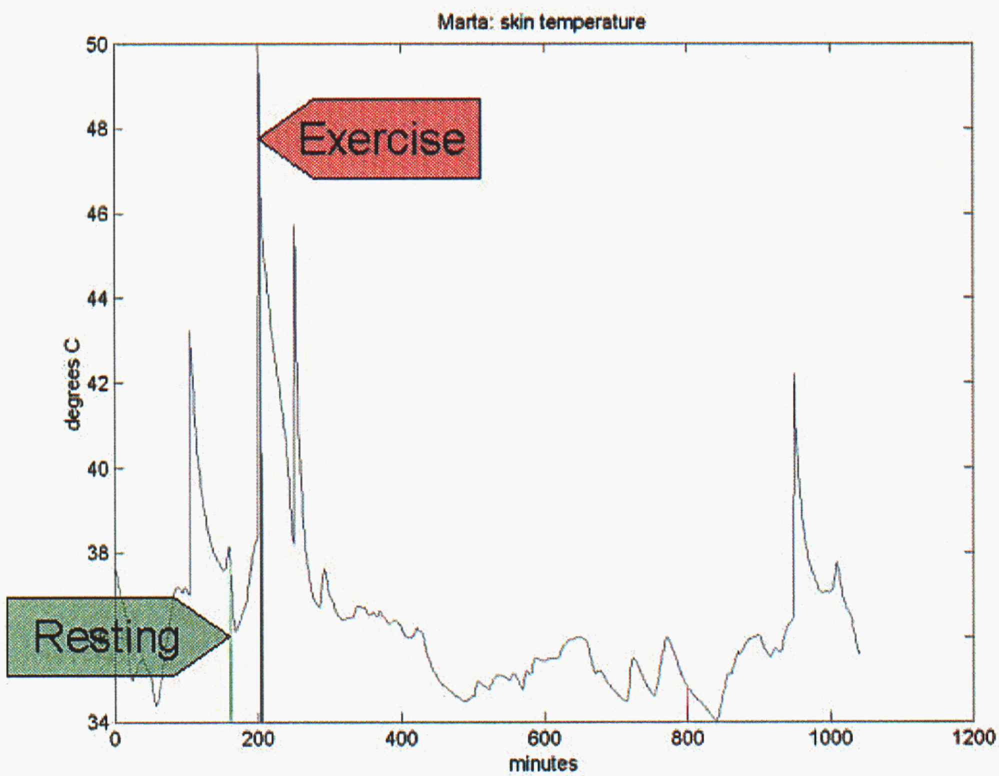

Figure 7. Heat temperature collected from Body Media armband.

We trained a SOM for recognizing physiological data from all sensors on the Body Media armband and providing personal awareness. The resulting output of the SOM plus clustering algorithm after training can be seen in Figure 8. The subject wore the Body Media armband physiological collection device for 24 hours in the collection of the data represented here; 14 data channels were utilized. The six differently shaded areas represent six clusters identified by the algorithm. Black cells are map locations of user-identified points. The subject in this case identified four activities of interest, which are represented by the single colored cells in the figure: jogging (pink), yard work (red), resting but not sleeping (black), and sleeping (yellow).

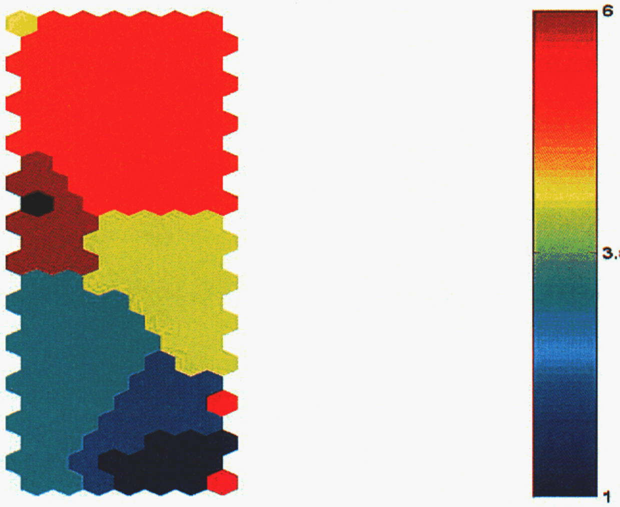

Figure 8. Initial output of clustering algorithm, before optional merging. Here, the algorithm created two extra classes. The data representing these classes can be examined, and the classes can be merged to each other, with other classes, or left alone. Points of interest are plotted: jogging (pink), yard work (red), resting but not sleeping (black), and sleeping (yellow).

In Figure 9, we show one possible outcome of the algorithm, after exercising the merge option. Here, classes 3 and 4 from Figure 8 were merged, creating five classes.

We then collected additional data from the same human subject on several later dates. The trained and clustered SOM did well at classifying the activities of an individual subject, while performing everyday activities. Furthermore, the scheme was able to successfully differentiate between seemingly difficult cases, such as sleeping versus reclining on the couch while watching television.

Next we collected sample data from another person doing similar things, *i.e.*, resting, sleeping, and exercising. The output of the algorithm was found to be highly individual. The original algorithm was trained using data collected on a young woman. Without retraining, we fed measurements taken from an older man through the network. There were real discrepancies between what the human subject was doing versus what the SOM identified. For example, when faced with the new data, the network claimed the man was always asleep, even though he may have been exercising at a gym. Proper results were obtained when a new network was trained based on the man's data. Further test subjects would be required to determine if such results are truly a trend. Additional subjects may show that each individual's physiological data and responses are unique (necessitating a different network for each person), or that similarities exist among groups of similar age and physical condition. Additional results can be found in [18].

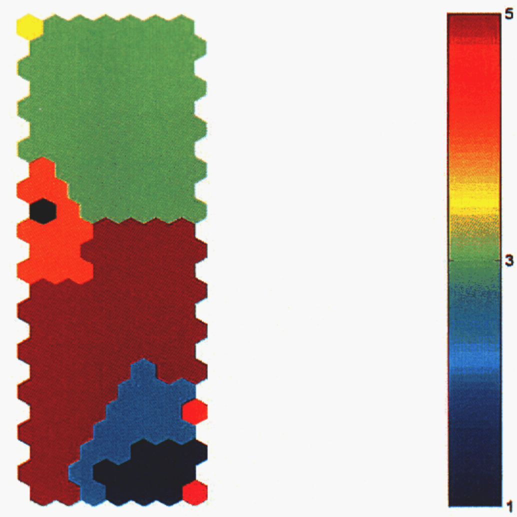

Figure 9. Merging applied to SOM in Figure 7 to produce five classes.

However, the fact that the SOM seemed to be highly individual reaffirmed our claim that a trained SOM provided customized personal awareness. Similar projects, such as the WPSM, use broad rules to distinguish situations, and hence, may not provide an adequate level of detail needed for true personal awareness.

8. Another Case Study

In collaboration with Dr. Steve Petruzello at the University of Illinois at Urbana-Champaign (UIUC), we collected data from two instructors at the Illinois Fire Services Institute at UIUC. The data was collected using a Minimitter 4-channel Mini-Logger Series 2000, a physiological data logger with 128K memory and heart rate receiver. While the Body Media provides a wider range of sensors, the Mini-Logger had been previously used in fire exercises, *i.e.*, in extreme heat, so we decided to collect heart rate and body temperature using this sensor, just to test our SOM algorithms.

The two individuals were instrumented by 7:30 AM each day (Tuesday-Friday) and the collection of heart rate and skin temperatures was continuous (a sample of each every minute) until approximately 5:00 PM. Because of the nature of the course, the instructors did a variety of things, ranging from very little (teaching in the classroom, watching the students during activities) to more strenuous (donning turnout gear, entering hot environments) physical activities. The resulting physiological measures showed a fairly sizable range as a result.

In Figure 10 we show the uniform distance matrix (u-matrix) for subject BB. The red areas represent areas of intense activity (high heart rate and temperature). The blue areas represent times of light activity. In Figure 11, we display the activities from day three for BB plotted directly on the SOM. Day 3 is the training data set as well, so this is data used to train the SOM. The color cyan is "classroom instruction", red is "drill supervision", magenta is also "drill supervision", but at a different time of day. Black is "live fire obstacle course". There were breaks taken during the black area, but we do not know when.

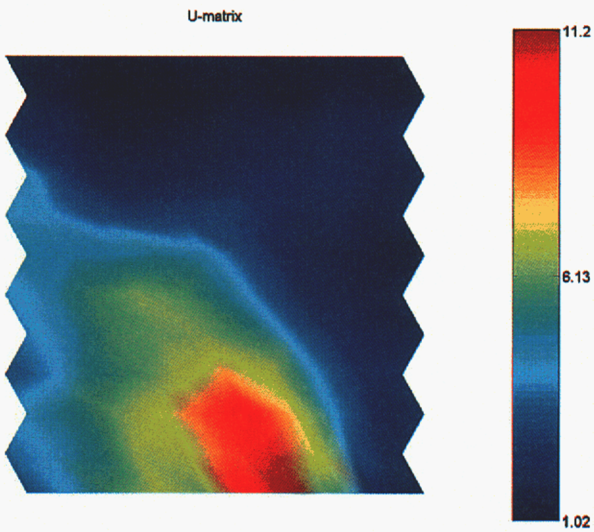

Figure 10. Uniform distance matrix (u-matrix) for subject BB. Red areas indicate areas intense activity while blue areas indicate times of light activity.

Figure 11 shows the cluster that the algorithm came up with. Brown is heavy activity, and blue is light activity. Because of the details we had, it made sense to classify in these two classes. The color map is the same as the previous figure. There are a number of live fire course points (black) plotted outside the heavy activity area, but only one drill point (pink) inside the high activity area. Again, we do not know when the subject took breaks. Finally, in Figure 12, we show the same subject's data from day 2, plotted on the SOM map trained with day 3 data. The color keys are the same.

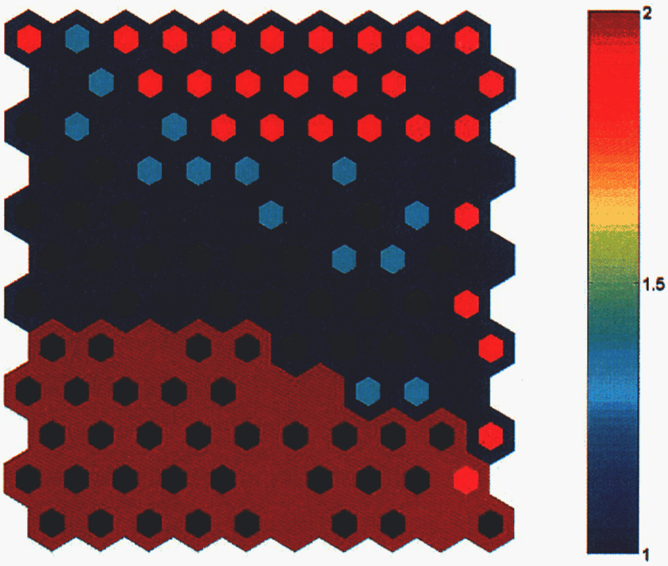

Figure 11. Cluster for Subject BB's data.

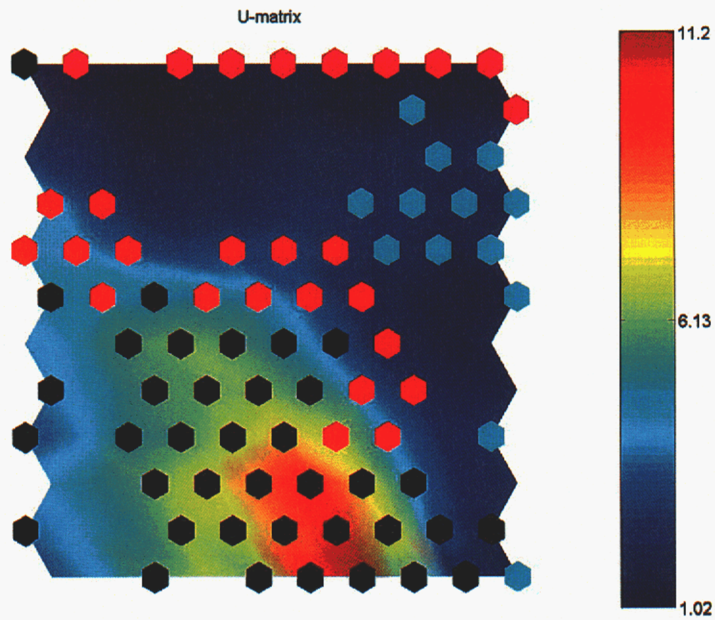

Figure 12. Subject BB's test data plotted on trained SOM.

In the fire instructor's data, we believe it does not make sense to classify the data in very fine-grained classes; rather, it makes sense to classify the data as "heavy" and "light" activity. Furthermore, we believe that the suite of sensors that the Body Media armband provides, *e.g.*, accelerometer readings, can help us make more informed decisions. For this case study, we had only heart rate and temperature data.

9. Conclusions and Future Work

We have developed an awareness tool that supports individuals and small teams in emergency situations. This tool provides both personal awareness and situation awareness and also decision making support to team leaders. This tool uses physiological sensor data to improve human and overall system effectiveness. We demonstrated this in a pilot exercise.

Novel features of this tool include a sensor-independent component for connecting heterogeneous sensors, a highly flexible agent architecture for team coordination, the coupling of a number of different types of intelligent algorithms to provide various levels of awareness and decision support on both personal processors and group processors, and a new clustering approach to interpreting physiological data and training SOMs. The clustering algorithm performed very well. The coupling of the SOMs and rules on the personal processor gave individuals a better sense of personal awareness.

As faster, smaller processors become available, the platform will be upgraded. We plan to employ a WPAN to reduce power, conserve space, and provide a better-packaged tool. These goals will be realized as new commercial off-the-shelf wearable sensors become available. We have not yet included environmental sensors in the mix. One such sensor of particular interest is Sandia's μChemLab [20,21]. At this time, we are developing and training intelligent algorithms to analyze the μChemLab data. μChemLab is a high sensitivity chemical sensor that can provide a broad range of environmental measurements and can support decision making during crisis and emergency operations.

Most of our future work will focus on the development of intelligent algorithms to demonstrate more complex scenarios of personal and situation awareness. For example, we plan to explore the use of fuzzy classification schemes in the SOMs.

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