Computer Assisted Space Medic

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COMPUTER ASSISTED SPACE MEDIC

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ABSTRACT

On the International Space Station (ISS) procedures for emergency medicine are addressed by referring to a hard-copy manual. This manual is typically over 1000 pages, is bulky for emergencies, and is printed in both English and Russian. While, the manual is substantial, it is unwieldy at best in emergency situations. This manual cannot be updated easily with new medical knowledge as it becomes available. Further, the communication with the qualified medical personnel at the Mission Control Center has substantial latencies, especially, the further astronauts venture into space.

With advances in information technology, several new avenues for improvements have become possible. Particularly, for the 21st century, hand-held devices and wearable computers afford the possibility of new knowledge navigation. Also, the ability to store and integrate, large quantities of all kinds of critical data in minimal space is necessary in the cramped environment of spacecrafts.

In this paper we propose an intelligent support system for on-board personnel. This system will combine imaging technology with data fusion, software agents, and neural network technology to provide an enhanced level of emergency medical knowledge One of the objectives in this architecture is to allow the system to function as a stand-alone system for emergencies as well as function with the Earth-based NASA medical team for other non-emergency related treatments. A component of an improved emergency medical support system is a dynamic electronic reference system, that is capable of being updated from Mission Control Center, as well as is adaptive to local conditions.

The goals of the system are, to interactively receive data from a patient or the on-board medic following standard practice. Further data or knowledge could be acquired from past medical history, operative history, examinations and investigative tests. Using available data the system helps in determining possible diagnoses and associated treatment procedures. Also, the system will determine what further investigative actions should be taken to focus on the patient. At the same time, the system learns diagnostic knowledge from the patient cases presented to it.

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BACKGROUND

The practice of medicine is confounded by severe restrictions as humanity reaches farther out into space. A Mars mission will have communication delays of up to 40 minutes making emergency support difficult. Current techniques of telemedicine will not be practical in emergencies due to the tele-presence requirement of a practicing physician. The National Aeronautics and Space Administration (NASA) has relied on what is now called "telemedicine" to treat any conditions that may arise during space flight. Current International Space Station (ISS) procedures generally involve the physician on the ground talking the astronaut through the assessment and treatment process. This is aided on board with a two-inch thick paper Medical Checklist and a kit of medical equipment. The physician uses voice communications with the astronaut being the eyes, ears, and hands of the doctor. The physician at the Mission Control Center (MCC) makes all medical decisions. Any specific diagnostic or treatment procedures are found in the Medical Checklist. The physician will simply refer the astronaut to a certain page and have him/her follow those procedures.

The drawbacks from such a system are that it is slow and is dependent upon radio communications that are filled with delays and blackout periods. Without the physician on the radio, the crew has little on-board medical expertise. There are physician astronauts, but there are not enough to go on every mission. Every mission has a designated Medical Officer that receives 40 hours of medical training, but in the overwhelming majority of missions the Medical Officer is not a physician. In comparison, at the State University of New York, a paramedic would receive 544 classroom and 636 clinical hours for a total of 1,180 training hours[1]. The user's own personal knowledge base and experience can be critical in emergencies during communication blackouts. If a physician guides the astronaut to the proper page, the astronaut can follow the procedures easily. Without a physician, the medical skills on any mission are limited and the astronaut will have to use his/her best guess as to which page in the Checklist to reference.

PROPOSED SOLUTION

Intelligent medical systems will need to be devised to support deep space flights of long duration. Current technologies have developed to where a combination of different artificial intelligent methodologies can be used together to fuse the data from multiple heterogeneous sources, creating a diagnosis and treatment path. This path will coach and/or assist a relatively unsophisticated user to complete emergency treatment. The system can be used in both "sickbay" and remote environments. It must be able to work with delayed Earth support as well as stand alone in cases of emergencies and communication failure. Anderson et al (2002) has outlined a Phase 1 project as a proof of concept for the artificial intelligence infrastructure that will be required for the foundation of such a system. This system will be able to grow and adapt to new devices and techniques as technology changes allowing the system's knowledgebase to continually advance.

A new vision and framework for advanced technological support in medicine is needed that specifically addresses the communications constraint during the long space flight and the subsequent Mars-based mission. This paper addresses a new approach for obtaining medical advice in space in both emergency and non-emergency situations. Figure 1 depicts the current situation on the International Space Station of the use of a paper medical manual. Figure 2 depicts

[1] State University of New York Stony Brook Paramedic Curriculum guide for 2001-2002

our proposed solution of integrating an electronic medical checklist with onboard lab equipment, patient history database(s), and mission control through agent based software. Our approach will result in a "Customized Medical Assistant" for astronauts using an individual's specific medical history rather than a generic reference. This is a key in creating an artificial intelligence architecture that is feasible with current technologies. (Diagnosis from a generic model will only become possible after numerous individuals and treatments have been entered over many years.) This customization will be an advantage for assisting the NASA medical team in the diagnosis of medical problems that may occur uniquely in space travel or planet side environments such as the surface of Mars. It is projected that by the time the Mars flight will be launched, there will be a large body of relevant medical knowledge that can be placed on board for local retrieval in emergency situations. One aspect of this distributed intelligence is that these knowledge modules will consist of a variety of Bots or software agents, which will cooperatively share in the intelligence processing tasks.

Figure 1: Current Situation - Static Paper Manual[2]

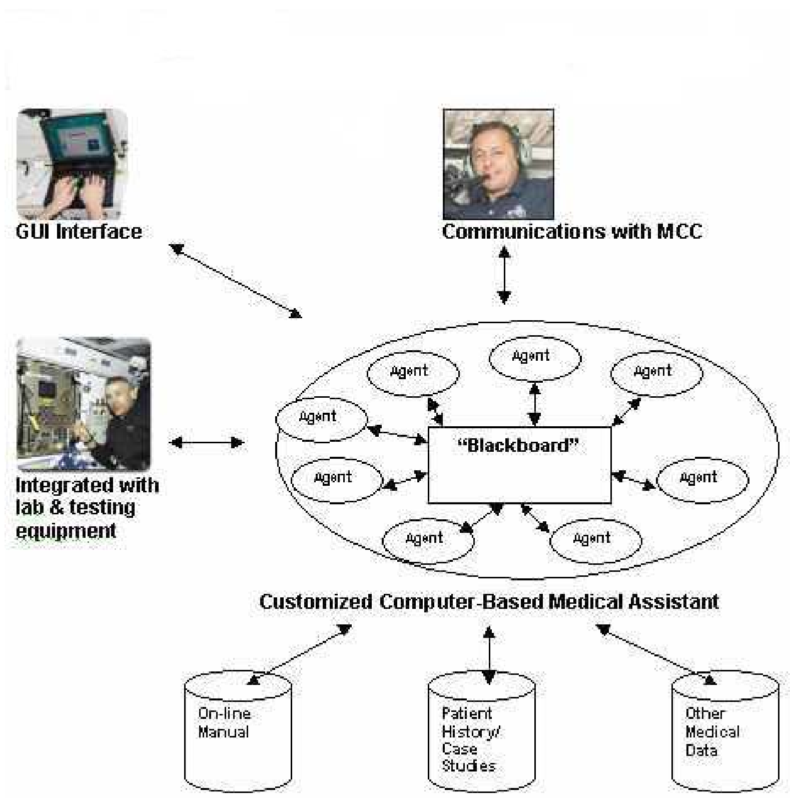

Figure 2: Proposed Dynamic System[2]

[2] Photographs courtesy of NASA web site.

Intelligent Decision Support Systems for medicine have been around ever since the first few expert systems were built. Some of these have been in use for a long time. However, in as intricately complicated as the human body is, there are no comprehensive and standard systems in operation. With advances in information technology, newer modes of incorporating data, information, and knowledge acquisition, processing, consultation, displays and activation are possible. Advances in various multi-media technologies rightfully support these into medical decision support systems. Our current application requires elements of the architectures of telemedicine, neural networks, multi-media, and in particular ultrasound and related imaging systems. In addition to agent technology (Liu, Zhong, Tang and Wang 2000), There are issues in medical decision-making conditioned by communication systems with long delays, and the difficulties of physically transporting a patient in a spacecraft to Earth, as one would in a terrestrial situation. Kazmi et al (Kazmi et al, 2000) addresses challenges associated with ultrasound in telemedicine, using wireless devices. Currently agent technologies are used in wide areas. Falasconi et al (1997) discuss multi-agent architectures for distributed health-care systems. Chen, Wolfe and Wragg (2000). Also, Katehakis et al (1999) present architectures for medical decision making with distributed multi-agent systems.

The resulting intelligent system's goal is to raise the care level possible with an individual who is first-aid level training to one comparable to an emergency medical technician or paramedic. This level would result in sufficient emergency treatment to save lives and create additional time to work within the communications delays and blackouts.

GENERAL ARCHITECHTURAL ISSUES

Our proposed solution is based on an earlier approach of Moreno et al (2001) of an agency of dynamic software agents, some with inferencing ability for different specific tasks to process a given emergency situation on board. All agents interface with a blackboard, a common approach in many artificial/ expert systems based applications. These agents are generic. Through an object-oriented framework, we can have subclasses of more specific agents if needed. These generic agents are:

1. An Acquisition Agent
2. A Screening Agent
3. A Laboratory Agent
4. A Treatment Agent
5. A Communications Agent
6. A Decision Agent
7. An Environment Agent
8. A Learning Agent

Figure 3 shows a general layout and interaction of these agents. The Acquisition agent interfaces with the User Interface, as well as with other data acquisition devices through the Lab agent. The layout of these agents has been kept with a low design complexity in mind. The purpose of the Communications agent is to marshal the needed data to/from the Mission Control Center (MCC). The Communications agent will be called upon to provide information as needed to the other agents about the status of the communications link, what delays could be expected for a round trip data flow and handling other details of the long delays in communication. The Decision Agent will have rules to help address medical contingencies in communication delays with respect to a diagnosis. The Communication Agent will have rules that deal with communication contingencies.

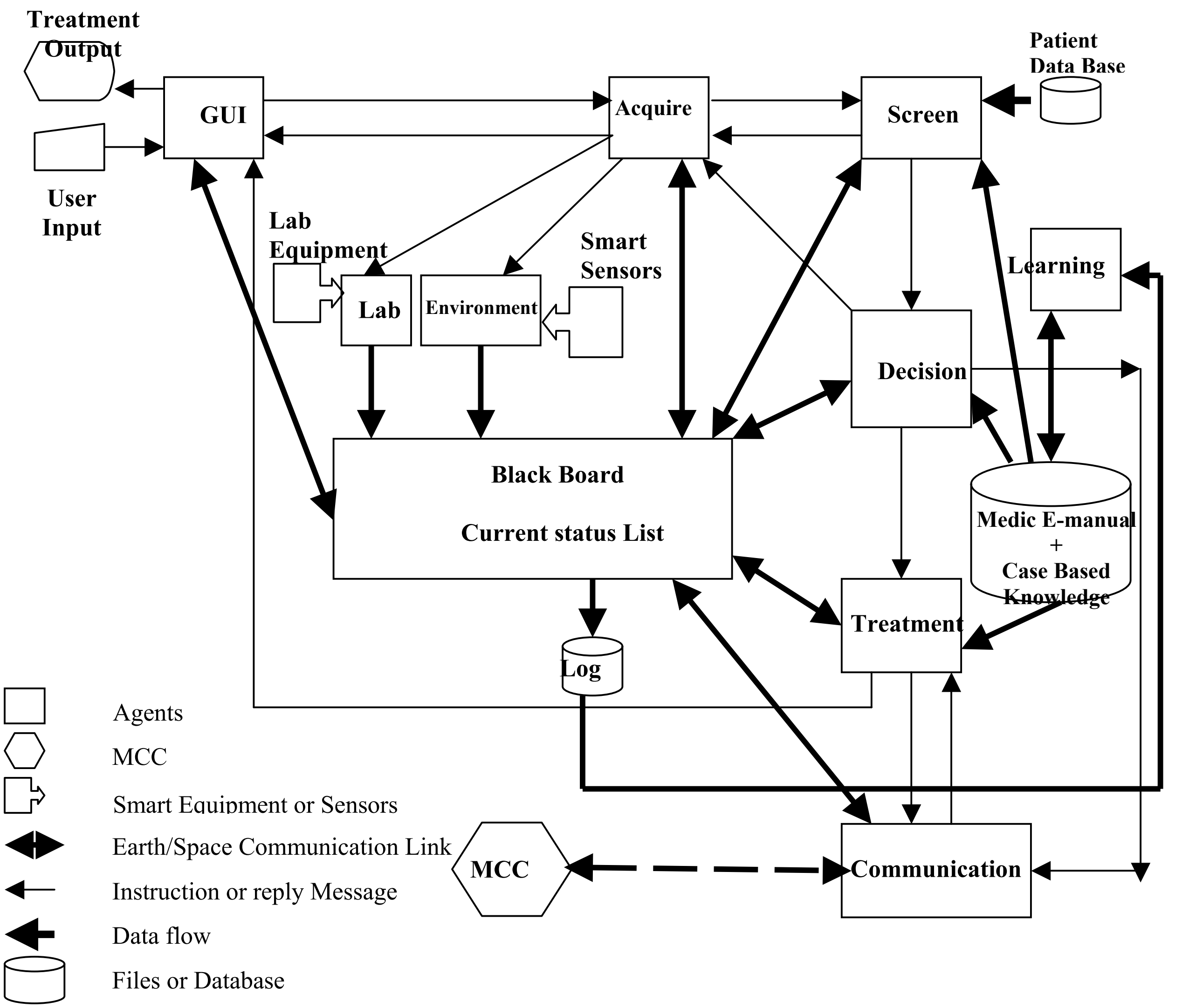

Figure 3: Agent Based Architecture for Autonomous Space Medic

The communications agent will also help in providing support for periodic updates to be made from MCC to the on-board knowledge base in the Medic Manual. When these updates will be done will depend upon the size of the updates and the urgency of the updates. During updates, routing of specific inquiries to MCC may be suspended.

The on-board architecture could also be multi-tiered for effectiveness. The architecture design should anticipate developments in hardware/software that could allow reasonable updates of the architecture.

INTELLIGENT AGENTS – ISSUES IN LEARNING

An intelligent agent in our system is given a minimum of background knowledge at the beginning, and it learns appropriate "behavior" from the user, past cases, from other agents, and from experts at MCC. The particular conditions that have to be fulfilled is that the use of the system has to involve a substantial amount of repetitive behavior. If the condition is not met, a learning agent will not be able to learn. This learning process is inspired by the metaphor of a personal assistant. Initially, an agent that is a personal assistant is not "knowledgeable"; it needs some time to become familiar with diagnostic decisions and treatment procedures. Gradually, with more medical problems being consulted and solved using the system, more knowledge would be stored for agents decision-making. This learning approach presents a satisfactory solution to the *trust* and *competence problems* of intelligent agents. While the agent gradually develops its ability, with the same dynamics the users of the system build up a model of agent's behavior obtaining more trust in the agent's explanations of decisions and actions. At the same time, the user follows how an agent acquires the knowledge it needs for later automatic decisions becoming more and more competent in the domain. A learning agent acquires its competence from different sources and in different ways:

- *Observing and imitating the user's actions and decisions* – The agent monitors the activities of users and the system for different scenarios, and keeps track of all actions during several sessions over longer periods of time. Based on these observations the agent finds regularities and recurrent patterns and offers to automate these or similar cases.

- *Receiving positive and negative feedback from the user and MCC experts* – An indirect feedback happens when the user or MCC expert neglects the suggestion of the agent and takes a different action instead. The user can also give an explicit negative or positive feedback for actions automated by the agent suggesting, " don't do this again" or " I prefer this diagnosis".

- *Receiving explicit instructions from the medical doctors at the MCC* – A medical expert can train the agent by giving it hypothetical examples of events and situations. Telling the agent what to do in those situations, what are the possible diagnoses and what kind of treatment to perform in these situations, teaches the agent.

- *Communicating and obtaining advice from other agents in the system* – If an agent does not know by itself what action or decision is appropriate in a certain situation, it can present the situation to other agents and ask for "advice". For example, the decision agent may ask the screening or treatment agents for additional retrieval, explanations and suggestions.

Acquiring the knowledge from different sources the agent gradually learns how to better assist the user. Through incremental learning the agents become more competent: they become more helpful, as they accumulate knowledge about the new medical cases and how the user together with MCC experts handle these situations. Also, the agents can be trusted: the user of the system is able to follow gradually and incrementally the agent's actions with its competencies and limitations.

Most of the inductive learning methods require significant amount of cases and situations to build the agent's knowledge. Therefore, we decided to build learning agents in our system using Case Based Reasoning (CBR) methodology. The benefit from the CBR approach is that the methodology can be applied with a small, or limited amount of experience and incrementally develop the performance adding more cases to the case base as they become available. The main argument is that users of our system, even the medical experts, do not have enough experience in space medical situations and actions. The database of space medical cases and corresponding decision/treatment processes will grow very slowly for the near future. Any simulated experiments will have questionable confidence and only real-world situations will represent a sound source of knowledge.

In general, CBR is a methodology for solving problems by utilizing previous experience. It involves retaining a memory of previous problems and their solutions, and by referencing these, solving new problems. In the situation where a previous identical case is retrieved, assuming its solution was successful, it can be returned as the current problem's solution. In the more likely case that the previous case is not identical to the current case, an adaptation phase occurs. The differences between two cases must first be identified and then the solution for the new case should be generated taking into account these differences [Pal 2000]. In most CBR systems, the CBR mechanism consists of two main parts: a) the case retriever, and b) the case reasoner. The architecture of CBR mechanism, build in our intelligent agents, is given in Figure 4.

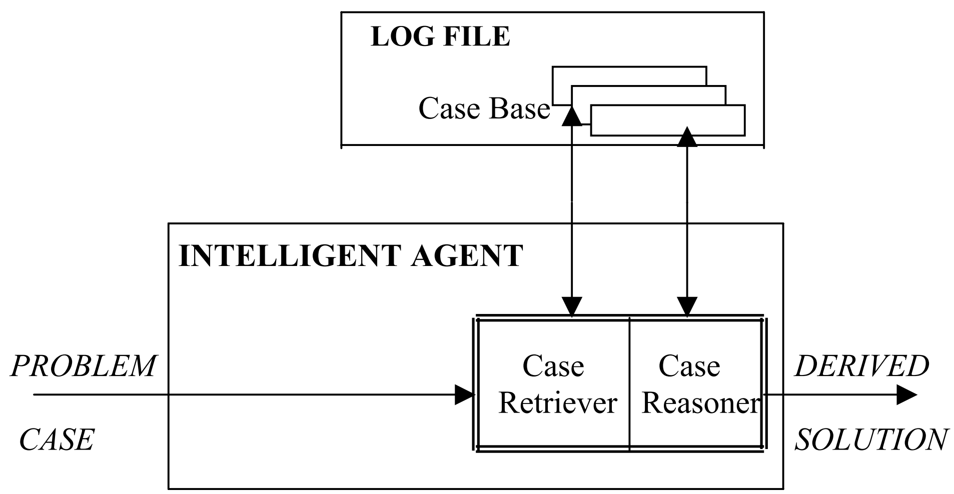

Figure 4. The Architecture of the intelligent agents CBR mechanism

The case retriever's task is to find the appropriate cases in the case base, while the case reasoner uses the retrieved cases to find a solution to the new problem with a given description. The reasoning involves both components determining the differences between the retrieved cases and the current new case, and modifying the solution appropriately to reflect these differences. In general, we refer to CBR as being applied to the solving of problems, but it can be used also in arguing a point of expert view or reminding to alternatives.

A case can be said to be the record of a previous experience. In our system the case represents a complex data structure including not only symptoms and signs of the patient but also diagnosis and detailed treatment. Each case is triggered with an event, but it follows this event in time including the patient's history. It is also essential to include in the case record the achieved measure of success, for the cases that have different degrees of success or failure. Because of the extremely complex data describing the case in the case base, we have to build an appropriate structure and representation of the log file as a source of data cases for learning. Although there will be the cases in the case base with missing or incomplete values, CBR mechanism is a reasonably successful in these situations.

In whatever format the cases are represented, the collection of cases itself representing a case base has to be structured in some way to facilitate the retrieval of the appropriate case when queried. While a flat case base is a common structure in most of the CBR applications, a hierarchical structure that stores the cases by grouping them can reduce the search process and increase its performance.

One of the weakest characteristics of the CBR methodology is determining weight factors for each attribute/feature of the case as a vital part of the knowledge base. In the situation when we do not have a case base or the case base is very small, estimation of the factors is a task for the medical experts. These values will represent only the initial settings, and, with the growth of a case base, an automatic procedure will be established for their modifications. Hybrid systems of learning are solutions that will be included in addition to CBR mechanisms for learning and tuning feature's weight factors. We are proposing artificial neural networks (ANN) methodology for learning these factors based on the available case base. After the ANN is trained with the given set of cases, the inputs of the network with large connecting weights might be considered as important features. The ANN may also analyze sensitivity, relevance, saliency, and activity as important characteristics of a case base improving the quality of the stored knowledge. Specific decision-making problems that are part of a new case analysis may be also solved using an ANN technology when a case base is large enough. ANN's for diagnostic classification or lab measurement prediction will be mechanisms build into an intelligent agent improving its knowledge-based performance.

Another concern is how the medical knowledge in the e-manual and the case based knowledgebase is validated. The interactions with MCC will provide mechanisms for validation as shown in Figure 4.

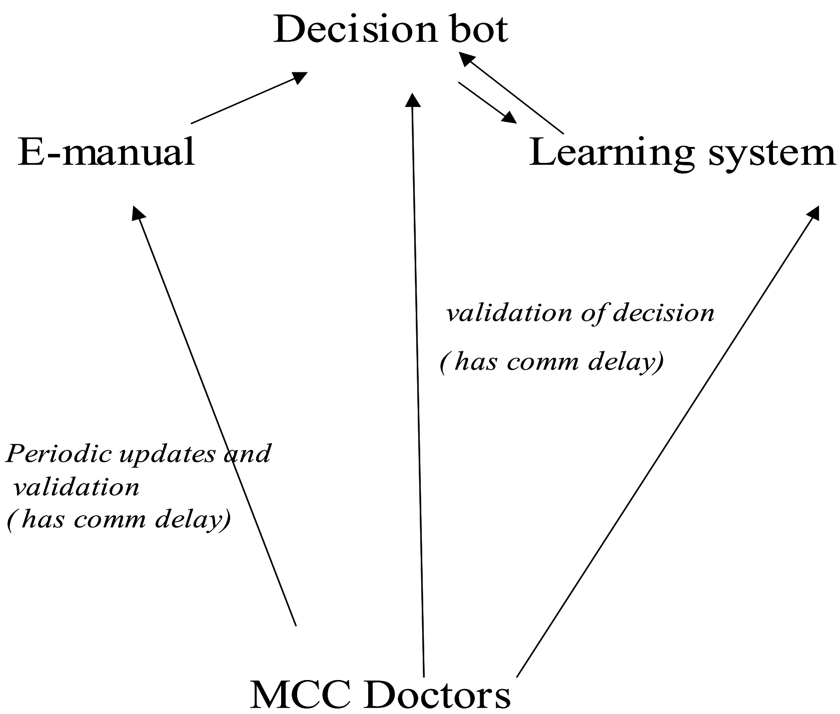

Figure 4: Knowledge Validation Process

FUTURE DIRECTIONS

The next step in this research is to devise a module for efficient knowledge capture and revision. Medical knowledge is a vast domain filled with fact, “best practices,” and opinion. Phase 2 of our research will improve the basic technologies developed in Phase 1 into a full working prototype and develop the basic structure for the creation and maintenance of a large knowledge base.

A system of this scope and intent requires the realization that development and evolution of the system and its processes, will continue long into the future. The nature of the architecture, the size of the domain in addition to a variety of unpredictable factors requires that every facet of the design be a continual learning process.

ACKNOWLEDGEMENTS

NASA has requested through the Small Business Administration’s Small Business Technology Transfer (STTR) program that certain Phase 1 recipients begin researching the many aspects of such a system. The research that is reported in this paper is a result of an on-going project supported by NASA. The project team consists of a joint effort between the Intellas Group, LLC and the University of Louisville.

REFERENCES

[1] Anderson, D., Belknap, M., Cui, X., Elmaghraby, A., Jacobi, D., Kantardzic, M., Ragade, R. (2002), A Distributed Agent Architecture for Human Operations in Space, for the International Society for Computers and their Application 11th International Conference on Intelligent Systems on Emerging Technologies.

[2] Chen, J.R., Wolfe, S.R., and Wragg, S.D., (2000) A Distributed Multi-Agent System for Collaborative Information Management and Sharing. Proceedings of the 9th ACM International Conference on Information and Knowledge Management, 2000, 382-388.

[3] Falasconi, S. and Lanzola, G. (1997). Ontology and terminology servers in agent-based health-care information systems. Methods of Information in Medicine, 36(1): 30-43.

[4] Katehakis, D.G., Chalkiadakis, G., Tsiknakis, M., Orphanoudakis, S. C., A Distributed, Agent-Based Architecture for the Acquisition, Management, Archiving and Display of Real-Time Monitoring Data in the Intensive Care Unit. FORTH-ICS/TR-261, October 1999.

[5] Kazmi, A., Arslan, B. R., Tulgar, M., Pedersen, P.C., Pahlavan, K., Cengiz, B., Advances in Wireless Telemedicine: Improvements and Challenges in Wireless Ultrasound, Proc. ITAB-ITIS 2000, pp. 9-16.

[6] Liu, J., Zhong, N. Tang, Y.Y., and Patrick S.P. Wang (eds.) Agent Engineering, in Machine Perception and Artificial Intelligence Series, Vol.43, World Scientific (2001).

[7] Liu, J., Zhong, N., Tang, Y.Y., and Wang, S.P., Intelligent Agent Technology - Introduction, International Journal of Pattern Recognition and Artificial Intelligence 15(3): 375-377 (2001).

[8] Moreno, A., Valls, A., Bocio, J. (2001), Management of Hospital Teams for Organ Transplants Using Multi-Agent Systems, Artificial Intelligence medicine, 8th Confenrence on AI in Medicine in Europe, AIME 2001, 374-383.

[9] Pal S. K., Dillon T. S., Yueng S. Y., Soft Computing in Case Based Reasoning, Springer-Verlag, London, 2001.