International Journal of Computing & Information Sciences Vol. 2, No. 3, December 2004, On-Line

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AdAgen: Adaptive Interface Agent for X-Ray Fracture Detection

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***Abstract**: In this paper, we have proposed an adaptive interface agent, called the AdAgen that collaborates with trained agents using neural network to build the software interface agent to detect fractures in long bones. The software agent that provides a semi-intelligent system learns by the "Customizer Dialog "from the user's interests, goals and general preferences. A major problem with the learning approach is that the agent has to learn from scratch and thus takes some time becoming useful. Secondly, the agent's competence is necessarily limited to the actions it has seen the user perform. When the proposed AdAgen is faced with an unfamiliar situation, the agent consults its peers who may have the necessary experience to help it. Thus, the proposed framework can alleviate the mentioned problems. The simulation results have shown how the neural network of the collaborating agents can help maintain the performance for automatic detection of fractures in leg radiograph.*

***Keywords:** Adaptive interface agent, software agent, x-ray images, customizer dialog, back-propagation algorithm (BP), self-oraginizing feature map (SOM) and fracture in long bone.*

Received: *April, 1, 2004* | **Revised:** *November 1, 2004* | **Accepted:** *December 21, 2004*

1. Introduction

Interface agents are computer programs that employ machine-learning techniques in order to assist a user dealing with a particular computer application. Despite the name, the interface agent is usually not the interface between the user and a computer program. Instead, it observes the interaction between the user and the program from the sideline and interacts with both the user and the program as shown in figure (1). Some interface agents are designed to train or teach the user, others can help multiple users to work together. Most interface agents are capable of learning and adapting to the interests, habits and preferences of the user [1]. Although they are successful in being able to learn their user's behavior and assist them, a major drawback of these systems is the fact that they require a sufficient amount of time before they can be of any use. A related problem is the fact that their competence is necessarily restricted to situations similar to those they have encountered in the past. In this paper, we present the adaptive interface agent that collaborates with other agents in the framework to help alleviate these problems. When faced with an unfamiliar situation, an agent consults its peers who may have the necessary experience to help it.

The remainder of the paper is organized as follows: section (2) is an overview of the related work. The proposed framework as described in section (3).The simulation of the proposed framework to detect fractures in leg radiograph is explained in section (4).

The experimental results are described in section (5). Finally, the conclusion and recommendation for future work is presented in section (6).

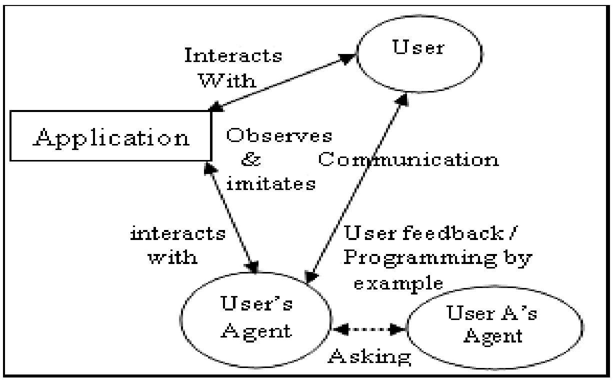


Figure 1. How Interface Agent work (adapted from Maes 1994 [1])

2. An overview of the related work

Previous interface agents have employed either end-user programming and/or knowledge engineering for knowledge acquisition. For example, [Lai, Malone, & Yu 1988] [2] have "semi-autonomous agents" that consist of a collection of user-programmed rules for processing information related to a particular task. The problems with this approach are that the user needs to recognize the opportunity for employing an agent, take the initiative in programming the rules, endow this agent with explicit knowledge (specified in an abstract language), and maintain the rules over time (as habits change etc). The knowledge-engineered approach on the other hand, requires a knowledge engineer to outfit an interface with large amounts of knowledge about the application domain and how it may be contributed to the user's goals. Such systems require a large amount of work from the knowledge engineer. Furthermore, the knowledge of the agent is fixed and cannot be customized to the habits of individual users. In highly personalized domains such as diagnosis medical image and news, the knowledge engineer cannot possibly anticipate how to aid each user in each of their goals. To address the problems of the rule-based and knowledge-engineered approaches, machine learning techniques have been employed by Dent et.al.1992 [3], Herman’s & Schlimmer1993 [4], Kozierok & Maes1993 [5] and Davis, *et al.* 1998 [6]. In the segmentation agent, the neural network is used to model each user’s segmenting imaging. The results described in [6] shown that the approaches used to interpret image, either model based approach or knowledge base approach are impossible. Each of them requires a significant amount of effort to describe objects in a well geometric primitive and to acquire the necessary knowledge base. In addition to the traditional techniques that have been advocated to image segmentation, each of them has its characteristic strengths and weaknesses. However, these techniques lack generality, adaptability and flexibility**,** since those methods of segmentation are hard to learn environment changes, so they are not suitable to co-operate with other process within multi-agent architecture**.**

While the learning approach enjoys several advantages over the others, it has its own set of deficiencies. Most learning agents have a slow "learning curve"; that is, they require a sufficient number of examples before they can make accurate predictions. During this period, the user must operate without the assistance of the interface agent. Even after learning the general user behavior, when completely new situations arise the agent may have trouble dealing with them. Davis, *et al.* 1999[7] proposed the blackboard architecture that contains the initial components of segmentation agent, feature extraction agent and categorize agent after trained using neural network to diagnostic classification of leg radiographs. In this system, each process has limited accessibility to a central set of hypotheses about the image and its sub-regions. Each time a hypothesis is modified, a global updating is allowed, allowing the different semi-autonomous modules to collaboratively refine the set of hypotheses about the source image. Such collaborative reasoning process require a mean of stopping when no hypotheses or when a specific module is satisfied, time consuming either in learning or after learning and need highly control unit to control each module in the blackboard architecture. In addition, this system needs to interact with users to enhance unclear cases through reasoning module, so, we proposed a new solution to these problems by implementing the adaptive interface agent manager in place of the control unit and collaborating with other agents that have the necessary experience to help it. When faced with an unfamiliar situation to get real time response.

3. The Proposed Framework

We have been proposed an adaptive interface agent to alleviate the mentioned problems, as shown in figure (2). The adaptive means that, such system attempt to modify their behavior to maximize the productivity of the current user’s interaction with the system. The major factors that distinguish interface agents from any other intelligent user interface are the fact that agents are proactive and enjoy a degree of autonomy. In addition to these general properties, it is usual for an interface agent to fulfill at least some of the following roles: assisting the user in communicating their task to the rest of the system, learning the user profile and selecting for presentation components of the system’s functionality.

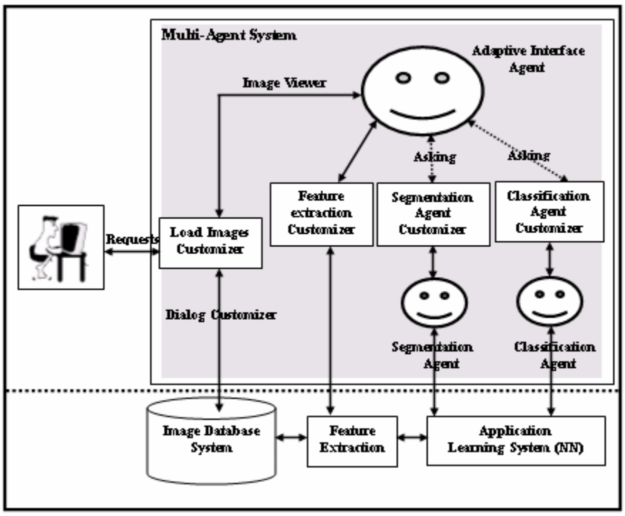


Figure2. The framework of an adaptive interface agent, the component under dashed line is out of the scope of this paper.

The framework for the AdAgen presented here allows the interface agent to observes, collaborate and monitors the actions taken by the user. In addition, the user learns it new ‘short-cuts’, and suggests better ways of doing the task (either in the selection of interested features, learning system using self-organizing map or backpropagation algorithms). Thus, the interface agent acts as an autonomous personal assistant, which cooperates with the user in accomplishing some tasks in the application.

How to Build a User Model: One of the principal problems in constructing an adaptive interface agent is gathering accurate information regarding the user's interests, goals and general preferences. Machine Learning techniques, which might be useful in achieving this, task [8]. Therefore, what is the learning technique might be suitable for an adaptive interface agent? The best choice depends on the domain the intelligent agent will work in as well as the environment. Since, our agent is long-lived and will perform similar tasks many times during its lifetime, then learning by neural network can be used to improve its performance and the agent used to control and solve the "black-box" problem of the neural network. We will use learning modes are typically by rote (or memory-based learning) which refers to the immediate and direct implantation of knowledge and skills without requiring further inference or transformation by the learner (i.e. agent) [9]. There for we will use feed-forward neural network and self-organizing map, because little memory, efficient in use and minimum error rate but self-organizing map unknown error rate and efficient in knowledge representation[10]. Then the user can be selecting the learning algorithm.

4. The Simulation of the AdAgen to detect fractures in leg radiograph

The medical imaging field has grown substantially in the recent years and has generated additional interest in methods and tools for the management, analysis, and communication of medical images. Many diagnostic-imaging modalities, such as x-ray, magnetic resonance imaging (MRI), digital radiography, and ultrasound are currently available and are routinely used to support clinical decision-making. By using medical imaging, physicians are able to glean qualitative and quantitative information about the anatomy and physiology of the patient. With these advantages, medical imaging has become central to medical diagnosis. Thus, with the advances in computer processing capabilities, it has become possible to approach the problem of automating diagnosis in medical imaging. In this paper, we will focus on the adaptive interface agent that help radiologist in automated diagnosis images.

The main frame of the adaptive interface agent is as shown in figure (3), which divided into four parts the top part, which contain toolbar that used to select the region of interest from image? The medial part contains JPanel plus Scroll bar that used to show the image analyses that have been resulted from each agent. The third part contains JPanel plus Scroll bar that used to image viewer (e.g. to ease the comparison, also used if the user decided makes the segmentation process interactively). The four parts contains the text filed to show the status of the agents.

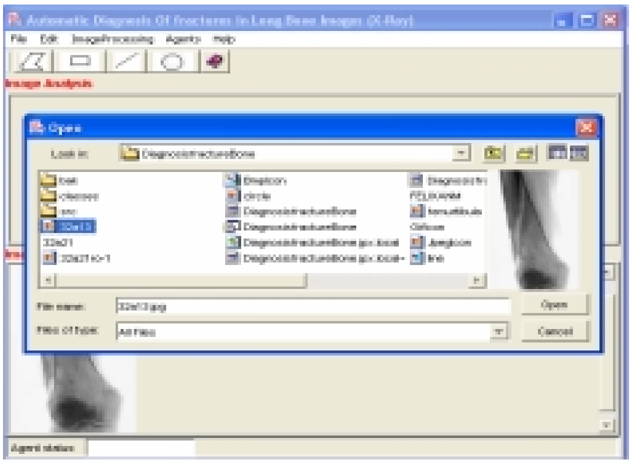


Figure 3. The AdAgen Screen Layout, with the Dialog Customizer used to load images.

5. Experimental Results

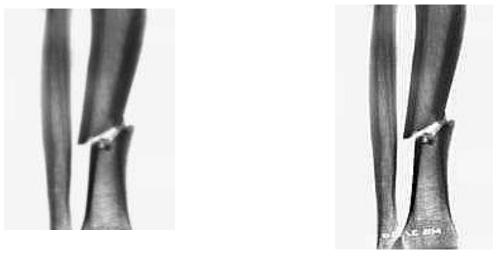
We simulate our system shown previously and tested it by the following experiments:

The first experiment: The user, can load image and then approximate edges based on the anatomical structure to detect fracture. This process is called manual process analogus to the real work of the radiologist. The results of this experiment are shown in figure(4). When we evaluated the results of the first experiment, we showed that the percentage of error increases if the severity of the fracture decreases as well as there is unkown percentage in case of unclear caeses. Then this method is not effiecient, in addition to the time consuming and need an expert radiologist in interpreting images when an expert radiologist is not available.

(a) (b)

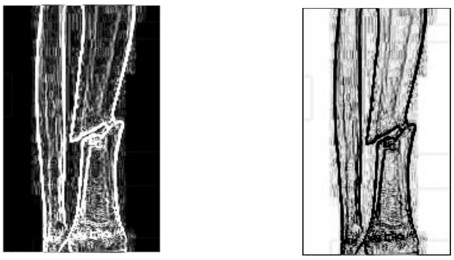
Figure 4. (a) The original image (b)The results of the first experiment.

In the second experimen:, the user segments the image first by, sharpenning , detectting edges and inverting. The next step the user lables the segmented images to identify the fractures. When we evaluated the results, we deduced that the average time increases by increasing the number of cases. This method cannot be able to learn the agent to take right decision autonomously, in additional the time consuming.



(a) (b)

Figure 5. (a) The original image (b)After Sharpenning (a).



(c) After edge detection (d**)** After inverting the applied to (b) resulted image in (c)

The third experiment: We have proposed the automated experiment to overcome the problems mentioned above as shown in the following experiment:

- Load images and select the regions of interest from each image.
- Extract features using feature extraction.
- The user call the segmentation agent customizer to create the new profile,add or remove features and then select the learning algorithm.
- The segmentation agent customizer, initiat the segmentation agent to begin training the neural network in separate thread and the control returns to the main frame.
- After training completed the segmented image is shown in main frame under image analysis. In some cases the user can enhance the results(if needed).
- Then the interface agent becomes able to segment images.

Although using this method the interface agent autonomously segments image, it takes amount of time more than the above methods. Therefore, we have proposed a collaborative solution to enhance the method above. While a particular agent may not have any prior knowledge, there may exist a number of agents belonging to other users who do. Instead of each agent re-learning what other agents have already learned through experience, agents can simply ask for help in such cases. This gives each agent access to a potentially vast body of experience that already exists. Therefore the proposed method used in automatic segmentation is as follows:

1. The user loads the image and selects the regions of interest.

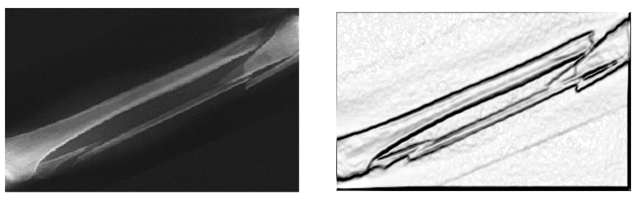
2. The user calls the adaptive interface agent to segment image.

3. The adaptive interface agent is responsible for:

- extracting the features from image by initiating feature extraction customizer that allows the user add or remove features.
- initiating the segmentation agent customizer that allows the user, select the learning algorithms.
- asking the segmentation agents to segment image.
- the segmentation agents submit the neural networks trained which segment images to enter the system through the dialog between segmentation agent customizer and the adaptive interface agent.
- the adaptive interface agent initiates the network parameters in the local network execution environment.
- Convert the features vector into a numerical representation for input into the network.
- Executing the network and deriving segmentation results.
- Display the segmentation results in the image analysis area (as shown in figure 3).

4. The user can visualize the results to enhance the unclear regions.

5. Similarly, these steps are repeated in case of automatic classification process (using classification agent) to discriminate between several types of fractures in long bones. The simulation results are shown in figure (6).



(a) (b)

Figure 6. Example of original grey level image (a)and its segmented form in (b) but after user, inverts it.

6. Conclusions and Recommendations for future work

This paper presented the AdAgen framework for learning interface agent that collabortes with other agents that have the necessary experience to assist radiologsit in detecting fractures in x-ray images. It has been tested with real world data. Simulation results have shown why we need the automatic learning incorporated in that system to improve the performance, reduce the time and enhance the agent's learning curve. The benefit obtained is the collaboration with other experience agents instead of relearning the agent after the end user requested it. Finally, in our framework we have shown that the customizer dialog allows each user to build a model of each agent's area of interest, and consults only those agents, which will be useful for each area.

Recommendations for future work

We will complete the sucessive steps of our system to automatic diagnosis of the fractures in long bone. Also, complete the automatic learning component with the aim to decrease the amount of time and enchance the percentage of error by adding several model of different neural networks trained with different architectures before initiating our system.

7. Acknowledgements

We would like to acknowledge Prof. Mostafa Mohamed Syiam and Prof. Mostafa Abd El-Aziem for their teaching, supporting, guiding and encouragement they provide me throughout my work.

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