Agent-Mediated Customized Training for Human Learning Performance Enhancement

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Abstract: Scaffolding is a well-established instructional approach that facilitates learning by incrementally removing training aids as the learner progresses. By combining multiple training aids (i.e. multimodal interfaces), a trainer, either human or virtual, must make real-time decisions about which aids to remove throughout the training scenario. A significant problem occurs in implementing scaffolding techniques since the speed and choice of removing training aids must be strongly correlated to the individual traits of a specific trainee. We detail an agent-based infrastructure that supports the customization of scaffolding routines per individual user. We describe the integration of this agent-based approach into a simulated augmented reality (AR) environment

Keywords: Agents, scaffolding, augmented reality applications.

1. Introduction

Learning by scaffolding [9] is an advantageous training approach since the learners can actively participate and clearly see their progress. Another advantage is that the learner is able to receive individualized treatment based on his/her training needs. This individualization, however, is also perhaps the biggest problem for the teacher since developing personalized supports and *scaffolded* lessons would be significantly time-consuming [11]. Furthermore, this problem is exacerbated if you consider a large number of trainees across multiple training scenarios. Another problem occurs considering the personality of the teacher. A proper scaffolding session requires that the teacher give up some of the control and allow the students to make errors [11]. Some conscientious teachers may find this difficult to do effectively. As a final problem, traditional manuals and guides in a learning environment do not include scaffolding instruction although the notion of scaffolding is independent of the actual training material.

In this paper, we proposed the use of intelligent software mechanisms or *intelligent agents* to help mitigate the impact of the aforementioned problems. Agents are software entities that have the knowledge of their environment and the innate capability to learn and adapt to their context given external stimuli. Agents are particularly well equipped in this domain because their operations are based on rules. As a learner performs within a scaffolded routine, agents can observe response times and errors and automatically reconfigure training routines to the respond to the individual learner. In addition, agents do not have the burden of human emotions. An agent can consistently mandate a training routine without the barriers imposed by empathy (as with human instructors) when learners make mistakes.

Probably the most significant benefit of using agents for scaffolding is the fact that agents can facilitate the separation of the concerns of training material versus training tactics. Typical training evaluation materials have problem sets combined with the corresponding *hints*. Without reconstructing this evaluative material, intelligent agents can control the delivery of hints and ultimately transform traditional training material into a scaffolded approach. To deliver these hints, we propose a scaffolding agent that controls hints over multimodal interfaces (i.e. graphical, textual and audible). In addition, we believe that by having multiple agents controlling various training tasks that an organization-wide scaffolding profile can be created.

The paper proceeds in the following section with a discussion of the related work. In Section 3, the intelligent scaffolding agent is described in detail with respect to design. In Section 4, we describe the implementation of this type of agent as a part of a simulated augmented reality (AR) environment.

2. Related Work

Separately the notion of scaffolding and multimodal training have been favorably investigated in many research projects [1][5][9][8][12]. However, as a combined approach these two techniques are suspiciously not well reported in published works. We believe these two approaches are quite compatible when considering the environment of computer-based training and training over some electronic medium. Multimodal approaches are excellent for providing hints that overlay regular, domain-specific instructions. Aist et. al. [1] used multimodal scaffolding approaches for training, but their focus was on the incorporation of emotions into training feedback. Several interesting results show the impact of emotions in their sessions. Contrastly, we propose an adaptive approach to creating scaffolding lesson plans in real-time that incorporate the results of many prior learners. These lesson plans are applied to the intelligent control of multimodal instructions.

3. An Intelligent Scaffolding Agent

A scaffolding agent can be defined as an intelligent software mechanism that uses the knowledge of its environment to reactively and proactively assist a human user with regards to incrementally learning a particular task or process. These aspects are similar to the traditional definitions of agents [6]. The focus of our work is, at least initially, to support the training employees in an industry environment. In our initial studies, we have tailored our approach to the manufacturing domain. This section discusses the agent architecture and our approach to representing a training session as a workflow process.

3.1 Agent Architecture

The scaffolding agent is composed of four high-level components, the *agent control component*, the *data management component*, the *rule engine component*, and the *multimodal interface component*. This logical architecture is illustrated in Figure 1. The agent control component executes the instructions that mandate the actions of the agent. The data management component contains the agent training-specific instructions as stored in an *agent knowledge base*. The agent knowledge base is a data repository that stores both the schema of the training tasks in addition to historical performance information of users that have completed the specific training routines. As the agent perceives a positive correlation in the way users respond to a particular scaffolding instruction, then a rule is stored in the *agent rule base* by the rule engine component. The rule engine incorporated in our experimentation is the Jess rule engine [7]. The agent control component manages the delivery of instructions using the multimodal interface component. As previously mentioned, the scaffolding agent is targeted for an augmented reality setting. At the time of this paper, the agent is still being integrated into the augmented environment, however we have experimented with the agent using a simulated AR environment modeled as a puzzle. Voice, text, and graphical instructions are used to assist the user in learning to complete a basic jigsaw puzzle. This proof of concept puzzle will be discussed in a later section.

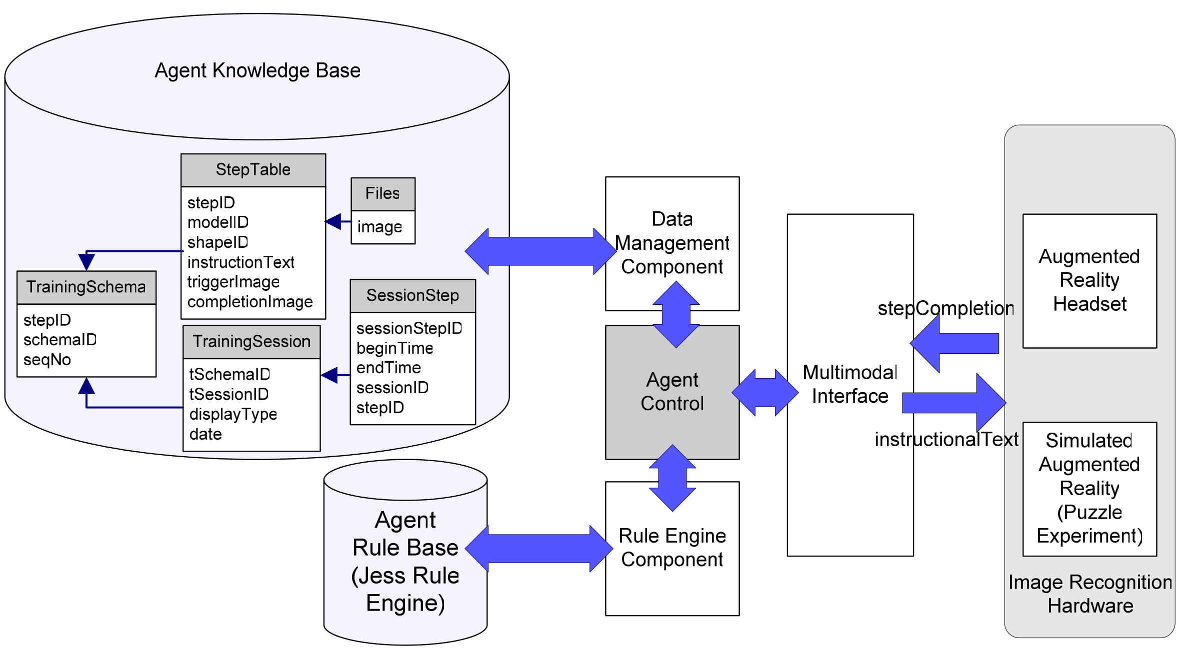

Fig. 1. Architecture of an Intelligent Scaffolding Agent.

3.2 Training as a Workflow Process

A workflow is defined as the implementation of a sequence of tasks to realize a specific process [2]. Typically, engineers in industry are trained to learn processes specific to their jobs. In a manufacturing domain it is important that workers both be competent in their work processes but also be consistent in the sequence in which they complete underlying process tasks. Consistency assures quality in the resulting product. Our workflow data model is illustrated in Figure 1 within the agent knowledge base. The main entity in the data model is the *TrainingSchema* itself. The *TrainingSchema* aggregates a sequence of workflow steps defined in the *StepTable*. In an augmented reality setting, the initiation and completion of a step can be identified when a particular image is captured. For example, if the placement of an automotive door on its hinges is the end of the task, then taking a snapshot of the door closed will produce a specific picture. By comparing the contours of this picture with an image on file illustrating the completion of the task, then the agent will be aware that the task (i.e. workflow step) is complete. Consequently, each step in the StepTable can be triggered when a certain image is captured. Image files are associated with each training step as a *completionImage*. The TrainingSchema entity is also associated to instances of training routine. The *TrainingSession* and *SessionStep* record specific performance and choice of multimodal display by training session and step, respectively.

The agent control module contains software entities that exploit the previously mentioned data model. The main object is a *WorkflowManager* entity that can consist of many *TrainingManager* objects. Each TrainingManager encapsulates a specific lesson plan. The TrainingManager is composed of objects that describe the specific scaffolding variations that were delivered to the user at each *Step*. Each step is defined by the specific training aids. In addition, each TrainingManager contains an object that records performance information (i.e. *MetricsManager*). The transition from one step to another occurs when a specific condition has been validated (i.e. *Validator*). In the case of augmented reality, an anticipated image is compared to a captured image by its contours and polygons (i.e. *PolygonMatcher* and *Contour Matcher*). The software entities for the workflow training approach are illustrated in Figure 2.

Implementing training as a workflow-based process is an important aspect of this approach, particularly considering the agents will customize training for each learner. The workflow paradigm facilitates the ability for the training scenario to have different paths based on the choice of the agent, also called a workflow *branch*. In addition, agents may have to make choices before and after each step in the training workflow when decided the next most effective training aid to present to the user (i.e. *exclusive choice* and *deferred choice*)

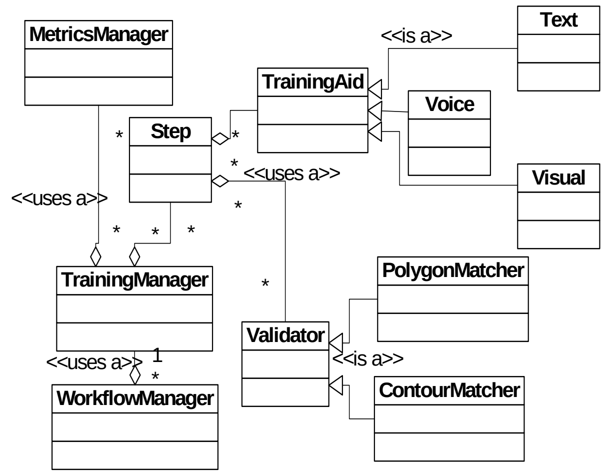

Fig.2. Object Design of the Workflow Training Software

3.3 Generating a Scaffolded Training Scheme

In generating a scaffolded training scheme, the metrics of multiple users are recorded using a straightforward equation. Weights are assigned to instructions based on the provided multimodal type, textual, t, verbal, v, and graphical, g. The completion time, Ct_i, that a user finishes a step, S_i, is also recorded given a specific number, i, of training process steps. A baseline time, Bt_i, represents the best possible time of completing a particular step based on measuring an expert user that knows the training case. Therefore, the training performance, TP_c, of a particular training case, c, is represented by

$$TP_c = \sum_{i=0}^{numSteps} \left(\frac{(t \cdot v \cdot g)Ct_i}{Bt_i} \right)$$

The reader should note that when all multimodal instructions are removed then the overall performance is equal to the optimal performance, OP_c (i.e. this is numerically equivalent to the total number of steps). The training performance equation takes into account the fact that some steps will take longer than other steps depending on the training case.

The agent attempts to map a user's performance to a specific scaffolding profile. The scaffolding profile is the most effective curve (i.e. minimizing user errors) for moving from the current training performance measure to the optimal performance measure. Several example scaffolding profiles are shown in Figure 3. In early experimentation, the scaffolding profiles have been generated by normalizing the curves of all users who have taken the system. We use this curve as the baseline for all experiments that we have run.

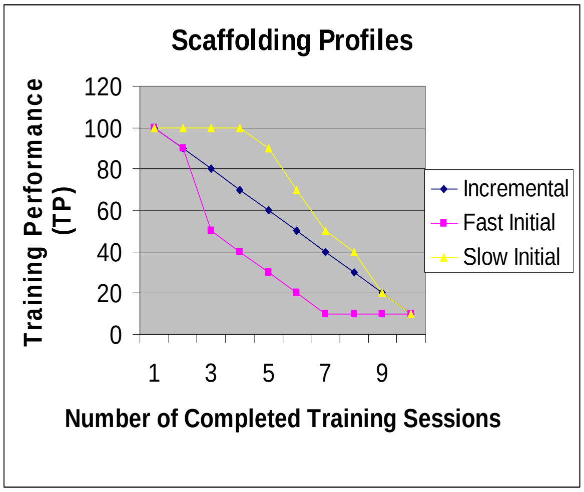

Fig. 3. Sample Scaffolding Profiles.

The agent randomly removes the multimodal instructions to target a training performance time that matches a time in the scaffolding profile. As the user learns the training case, eventually there will be steps that do not contain any training aids. At this point it is possible for the learner to make errors. The agent randomly varies the declining choice of aids to match the training performance of the case when an error occurs. Thus, the user repeats the training case at the same level of assistance and continues to take this case at the same level until it is completed without error. Multimodal instructions will slightly vary in each repetition. This repetition is recorded in the user's profile and ultimately enhances the entire scaffolding profile. The scaffolding profiles in Figure 3, shows how three different types of learners. The *incremental* learner can continue to learn more about the process in a consistent, almost straight-line manner. The *fast initial* learner moves quickly with regards to removing redundant training aids but learns much slower once training aids are removed. The *slow initial* learner has a difficult time grasping the task at first, even with aids, but later starts learning more quickly with experience. Once multiple user profiles are recorded, then the agent can compare curves to see similarities and differences. We suspect that the curves of a particular demographic will be similar, and the agent can then normalize a number of curves to get an aggregate scaffolding profile. This feature would allow agents adapt a scaffolding profile within a particular organization. This profile will evolve with time and with the entry of new employees.

4. Simulated Augmented Reality: A Proof of Concept System

The scaffolding agent was designed to be integrated with augmented reality headsets to provide advanced pedagogical support using multimodal instructions as delivered by the headsets. The agents provide enhanced human learning. As a first step, we have developed an emulated augmented reality approach. Using the Java programming language we developed an application that trains a user how to complete a jigsaw puzzle with the assistance of various multimodal instructions (illustrated Figure 4). The jigsaw puzzle is connected to and controlled by our scaffolding agent. Users have the ability to drag pieces to a specific location, and the puzzle will lock the piece in place as the conclusion of the step.

The puzzle is slightly different than a traditional puzzle. In a typical jigsaw puzzle, the person must recognize where pieces fit based on the visual patterns within each puzzle piece. In this application, placement is based on the color (of the puzzle piece) which is correlated to a specific region within the boundary of the puzzle. A user must learn the regions first then learn the order in which the regions should be populated with puzzle pieces.

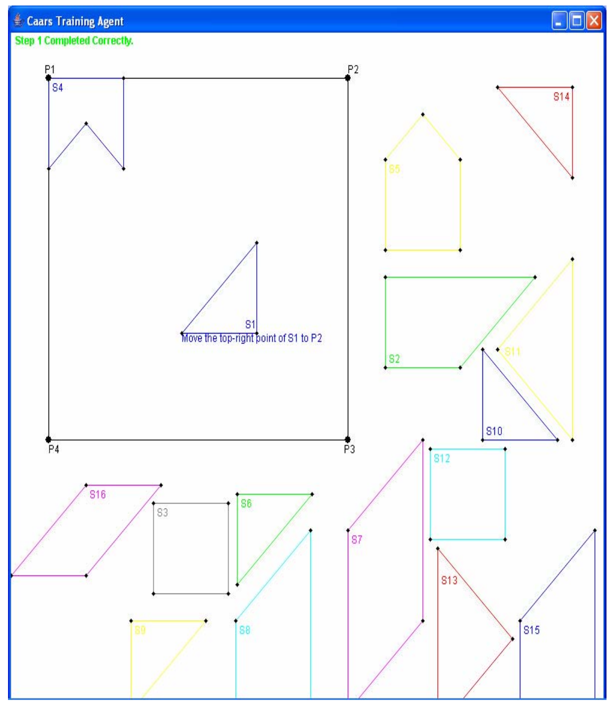

Fig. 4. Simulated Augmented Reality Environment with Multimodal Instructions.

At the initiation of the puzzle and at the completion of each step, the user is receives some combination of text instructions, visual instructions (represented by a dynamic arrow), and voice instructions. The illustration in Figure 4 shows a user in the process of placing piece, *S4*, in the second step while receiving voice and textual instructions. The rectangle having points P1 through P4 is the boundary of the puzzle. Table 1 shows a sample of data captured for the prior completed step for the puzzle piece, *S4*.

Table 1. Sample Training Performance Statistics.

Step 1 Statistics	
Start Time:	12:10:05
End Time:	12:10:11
Scenario Time:	00:00:20
Errors:	0

5. Agent-Mediated Control Measures

As discussed in Section 3.3, an agent can control the rate in which scaffolds are incrementally removed from a human user. We have found that three measures are most important when determining a specific learning curve for an individual. Those three measures are:

1. *The completion time of each of the training trials.*
2. *The location time of the user (i.e. the time between placing a piece and clicking on the next piece).*
3. *The step-by-step completion time.*

Figures 5, 6, and 7 show the graphical displays of the aggregation of a 6 users that have used the system in our initial experimentations. These figures represent the trial time, recollection time, and completion time of each step, respectively. These times related to a user that received all hints for five trials. With regards to trial time, users attempting to increase their performance tend to move quickly on steps that they learned early, but this could not be sustained when attempting to concentrate on subsequent step in later trials. Several data points in both location time and completion time did not correspond with the trends. The scaffolding agent was developed to normalize and correct for user behavior that does not follow an anticipated trend.

6. Discussion

In present work, we are matching the baseline curves with true scaffolded sessions. We have created 2 different puzzle layouts and are able to vary the sequence of steps and colors of puzzle pieces for any variation. We have run a number of experimental cases using this approach and have found that users almost immediately are able to operate the application. Considering just the authors (no specific demographic represented), the fast initial profile shown in Figure 3 is most relevant. We are currently implementing an experiment to understand what scaffolding profiles are most effective across various demographics (age, race, sex, and subject of academic study). We believe results from this future work will impact how scaffolding schemes are created in variety of settings (e.g. the classroom (K-12 or college), the industry setting, or even for elderly care).

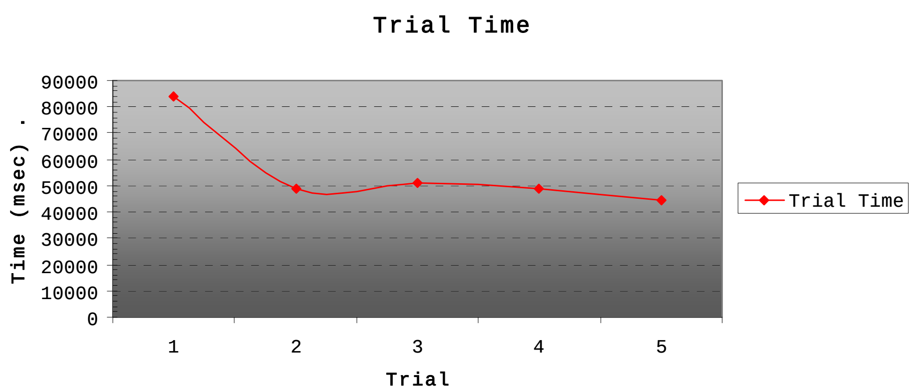

Fig. 5. Baseline Curve for Trial Time of Typical Users Comfortable with Personal Computers.

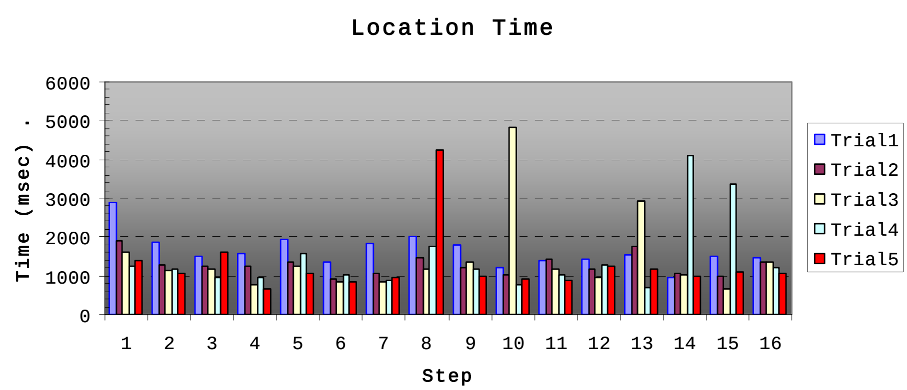

Fig 6. Baseline Results for Location Time of Typical Users Comfortable with Personal Computers.

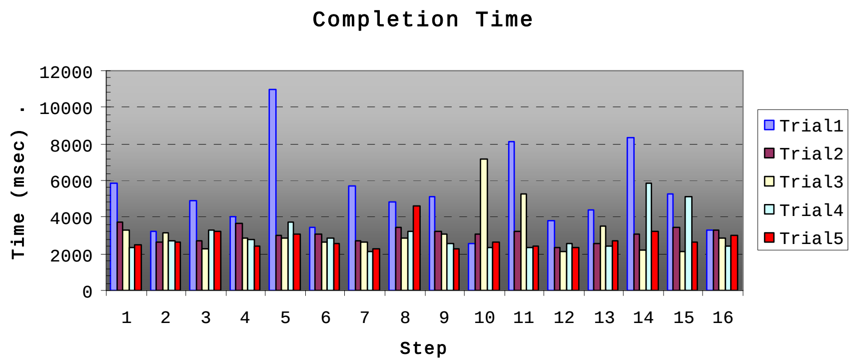

Fig. 7. Baseline Results for Step Completion Time of Typical Users Comfortable with Personal Computers.

7. Conclusion

This paper contributes an infrastructure that supports the integration of multimodal instructions and scaffolding generation techniques using intelligent agents. This approach has been customized to the manufacturing domain with multimodal instructions being delivered within an augmented reality environment. This is one of few studies that combine this set of technologies for the advancement of human performance in learning. In our present work, we have a number of on-going studies that investigates the correlation of effective scaffolding for different demographics. In addition, our agent approach is being integrated into a true augmented reality environment to support automotive manufacturing workers in the factory environment. A limitation of this approach and subject of future work is the strong connection of this approach to text, graphical, and verbal cues. In future work we will investigate other modes for instruction. In addition, concrete experiments with experimentation and control groups are ongoing.

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