Practically intelligent agents aiding human intelligence (Extended Abstract)

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ABSTRACT
Practical intelligence is gained by doing. In this project we offer a technique which allows software agents and humans to learn by doing. The human trainer, that is the domain expert, directly interacts with the system to create new scenarios and learning experiences for the trainee. As they interact with the system, the system acquires knowledge from the trainer which can be transferred to the trainee. For this purpose, we employ a hybrid case and rule-based knowledge acquisition and representation technique known as Ripple Down Rules.

Categories and Subject Descriptors
I.2.1 [**Applications and Expert Systems**]; I.2.6 [**Learning**]: *Knowledge acquisition*; I.2.11 [**Distributed Artificial Intelligence**] *intelligent agents*; K.3.1 [**Computer Uses in Education**] *Computer-assisted instruction (CAI*

General Terms
Design, Human Factors

Keywords
Knowledge Based Systems, Ripple Down Rules, Virtual Reality, Training Simulation, Intelligent User Interfaces, Border Security, Artificial Intelligence, Experimental, (Virtual) Agents, Believable Agents

1. INTRODUCTION
Our current project involves the development of an immersive training system to provide practical experience to trainee customs/immigrations officers without the associated risks of on-the-job training. We seek a solution which allows us to acquire, maintain and validate knowledge in the context of different training scenarios that support flexible and varied interactions between the user and system. To address the problems of scenario and knowledge creation, maintenance and adaptability we allow users, typically the trainer or domain expert, to author content and add knowledge themselves once a trained computer specialist has created the base scenario. Novelly, scenario authoring and knowledge acquisition are performed by the trainer while interacting with an existing scenario thereby providing context and outputting a library of scenarios in order to address some of the inherent difficulties associated with acquiring knowledge in general, and tacit or practical knowledge/intelligence in particular.

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For learning and learning transfer to occur, the training simulation needs to be believable. Agent technology plays an important part in making software (with flow on effects to the associated hardware) more believable. Loyall [7] has defined a set of characteristics of believable agents which includes: personality, emotion, self-motivation, change, social relationships, consistency of expression and the appearance of being alive as evidenced by being reactive, responsive, situation aware, and goal-driven. Johnson et al. [5] list the following factors related to believability: Situated Liveness (the character appears aware of their environment); Controlled Visual Impact (the extent of the movement/change); Complex Behaviour Patterns (simple behaviour is uninteresting and seemingly mechanical); Natural Unobtrusive Behaviour (like blinking or breathing). Additionally, many researchers see that a key to believability is embodiment requiring congruent body gestures, facial expressions, intonation, gaze, posture and language [3].

Believability can be measured along two distinct dimensions: visual appearance and behaviour. Researchers interested in believable animations (such as [1]) have long recognized that visual fidelity is less important than behavioural believability. Going beyond appearance, emotional awareness on the part of the agents has been found to be central to deriving a more realistic human-avatar interaction response, as emotions are a distinct characteristic of human like intelligence [2, 8]. Also, relevant is the body of work on socially capable (pedagogic) agents who act as peers or tutors guiding the learner through the learning material or environment (see [4] for a comprehensive review). With the exception of emerging work on empathic and listening agents, due to the difficulty of simulating actual intelligence, the majority of believable agents are designed to *appear* emotionally or socially intelligent, when in reality they have may have little or no knowledge of the user or reasoning abilities about how to act in a social situation.

We thus suggest a less-considered third dimension of believability: reasoning or cognitive processing. While reasoning could be viewed as part of the behaviour dimension, in addition to agent reasoning we include other knowledge processing and reasoning about the training environment and domain needed by the system to support experiential learning environments.

2. ACQUIRING PRACTICAL KNOW-HOW
To support incremental knowledge whilst experiencing a scenario, we use the knowledge acquisition and representation technique known a Multiple Classification Ripple Down Rules (MCRDR)

[6] which captures knowledge in context by locally patching rules (via the use of exceptions) in response to a new/changed situation deemed to be incorrectly classified. In the approach, the software developer would work with the domain trainer to set up a number of initial scenarios. Later, the trainer can independently interact with the base scenarios to add new scenarios and knowledge as exceptions by suggesting alternative outcomes, input variables, actions, objects and so on.

Knowledge is acquired as follows. In the airport security domain, a domain expert may be presented with the following scenario:

Scenario 1: A 27 year old female with no luggage is at the customs desk. She claims she is here for a week-long holiday.

The expert may then be asked how much of a risk the passenger in the scenario represents, and what action the customs officers should take and why. The expert may say that because the passenger is between 18 and 30 years of age and they have no luggage, they represent a high risk and therefore the customs officers should question the passenger further. This scenario will then be associated with the following rule:

IF 18<age<30 AND luggage = 'none' THEN risk = "high" AND action = "question the passenger"

When another scenario is presented to the expert, the RDR system will use the rules it already has to make its own conclusions about the scenario which the expert can then either accept or reject. If the expert rejects the system's conclusions a new rule will be created which will be an exception to the rule the system used in making its conclusion.

By using RDR, eventually a large rule base will be built by the domain expert, and the system will be able to make more accurate conclusions about a scenario based on the knowledge captured by the expert. A ripple down rule base is represented as a tree with each rule represented as a node in the tree (Figure 1). When a scenario is presented to the RDR system, it will move down the tree visiting each rule that applies to the scenario. When the system can no longer move to any new rules, it will present the conclusion in the last rule it visited. A new rule being added to the rule base results in a new node being added to the tree. The parent of the new node or rule will be the last node (or rule) in the tree that the system visited before making its conclusion.

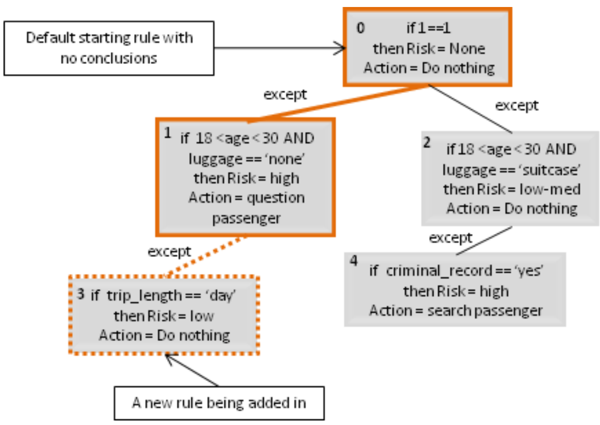

Figure 1. RDR tree with 5 rules

For example, Fig. 1 illustrates the nodes the system has visited in order to calculate the conclusion to scenario 2 (outlined in bold). The system first visits the default rule (which is always true and draws no conclusion or the default conclusion) then visits rule 1, the first rule that applies to the scenario. After this, the system has nowhere further to go and presents the conclusion to the expert. The expert then chooses to add a new rule, rule 3 (dotted line) which is an exception to rule 1. Thus, the next time a scenario is presented to the system that has a passenger between the ages of 18 and 30 making a day trip with no luggage, the system will be able to progress to rule 3 before making a conclusion.

3. CONCLUSIONS

We have conducted a small usability pilot with four participants who were successfully able to use the system to interactively add knowledge. We will conduct a larger study when we finish allowing the trainer to change characters, objects, dialogue, actions, etc on the fly.

We acknowledge the importance of non-verbal behaviours, emotions and social capabilities in the detection of suspicious passengers which is relevant to our airport security scenarios. While we can handle basic gestures such as fidgeting, covering ones mouth while speaking, etc., which have been found to be relevant in this domain [3], our simulations are far from what could be called realistic and rely on advances by other researchers in these areas. Our focus has been on acquiring and utilizing the knowledge relevant to the training environment so that the reasoning of our agents and scenarios will be believable (i.e. credible and appropriate) and support the human trainee to acquire practical intelligence related to the domain.

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