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Representing Uncertainty in Computer-Generated Forces

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***Abstract*—**The Integrated Performance Modelling Environment (IPME) is a powerful simulation engine for task simulation and performance analysis. However, it has no high level cognition such as memory and reasoning for complex simulation. This article introduces a knowledge representation and reasoning scheme that can accommodate uncertainty in simulations of military personnel with IPME. This approach demonstrates how advanced reasoning models that support similarity-based associative process, rule-based abstract process, multiple reasoning methods and real-time interaction can be integrated with conventional task network modelling to provide greater functionality and flexibility when modelling operator performance.

***Keywords*—**Computer-Generated Forces, Human Behaviour Representation, IPME, Modelling and Simulation, Uncertainty Reasoning

I. Introduction

HUMAN behaviour representation (HBR) refers to computer-based models that mimic either the behaviour of a single human or the collective actions of a team of humans [1]. Most Computer-Generated Forces (CGF) approaches used for military simulations lack plausible support from the human sciences. In a number of cases, these approaches have been found to be brittle, producing implausible behaviours for even minor deviations from the design criteria, and have insufficient representation power to provide adequate performance, particularly for training simulations. Models of perception, cognition and behaviour moderators (such as physiological and psychological stressors) from the human sciences are thought to be a means of extending a pure Artificial Intelligence (AI) approach to create a more plausible representation of observed behaviour for the military operators that the HBR is replacing [1].

Rule-based approaches are dominating the current human behaviour representation and used in various applications of CGF [1]. Examples include the situation awareness for aircraft and pilot simulation [2]-[6], threat event detection [7], and decision-making in combat pilot target selection [8], land forces [9] and navy tasks [10].

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Propositional-logic-driven systems are appropriate, in particular, for deterministic parameters or system models. However, many parameters related to environment, cognition and moderators are uncertain, such as intentions of enemy forces, or operators' emotions.

The Integrated Performance Modelling Environment (IPME) is a powerful analytical tool for task execution and performance prediction using discrete event simulation. IPME constrains task execution by providing an interface to incorporate human performance models. IPME has imbedded attentional and workload models that affect the flow of tasks. Unfortunately, it lacks high-level cognitive tools such as memory and reasoning for complex tasks undertaken by simulated military operators. The Simulated Operators for Networks (SimON) project [11] is attempting to extend IPME and develop architecture for modelling military personnel in CGF that can readily add human science information to HBRs.

We proposed a representation [12] supporting various reasoning in SimON. This approach can accommodate deterministic and uncertainty reasoning for simulations of military personnel with IPME. It is also able to deal with the impacts of behaviour moderators, for example, personality and emotion, in variable levels. The implemented reasoning system interacts with IPME in real-time to support decision-making and reasoning within simulated tasks.

This paper focuses on the uncertainty representation of simulated operators in SimON. In Section II, we will analyze uncertainty in CGF and review the systems with uncertainty reasoning in military applications. We will, then, in Section III, introduce a representation approach for uncertainty reasoning in virtual operators. Section IV will deal with the military applications with our approach. Section V will conclude our efforts.

II. Uncertainty in Computer-Generated Forces

Uncertainty exists in most military activities and simulations of these activities should incorporate this uncertainty when predicting the performance of personnel who may be involved in areas as command and control, piloting military aircraft, remotely controlling unmanned vehicles, directing helicopters during landing on ships, or search and rescue. In many cases, commanders cannot get exact and deterministic situation information, such as, strength of adversary forces. It is also hard for pilots to foresee weather

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conditions or potential threats. For an unmanned vehicle controller, the data related to an upcoming situation, e.g. terrain shapes and obstacles, is often vague. The decision-making process for a landing safety officer directing a helicopter to land on a rolling ship is complicated because many factors are uncertain, for instance, the helicopter pilots' technical skills or the stability of the flight deck. In search and rescue, there are also many imprecise factors, such as the exact position of a target.

Behaviour moderators are conditions or factors that affect behaviour, such as physiological or psychological state. It is difficult to measure many subjective behaviour moderators, such as emotion and personality, with deterministic values.

A variety of researchers have explored uncertainty representation in military simulation. In the simulation of command and control area, fuzzy logic [13], [14], [9] and probabilistic methods [15]–[18] are being used for situational assessments and decision-making. For pilot and aircraft simulations, a number of projects assist pilots' situation recognition and decision-making [19]–[22]. Some other examples use uncertainty methods for helicopter control [19] [23] and diagnosis of faults [24]. For unmanned vehicle control, some projects use fuzzy and other uncertainty methods for keeping safe speeds [25], obstacle avoidance and path control [26]–[29]. Richards' efforts [30] demonstrate the potential using fuzzy logic and neural networks to predict the trajectory of a landing helicopter. In the search and rescue area, a couple of researchers simulate target positioning with the Bayesian method [31] while others have used fuzzy logic to plan rescue activities [32]. Fuzzy reasoning has been used to assess the ease of traversing terrain [33]. Picard proposed a theory called affecting computing [34] that deals with the recognition and effect of emotions using the hidden Markov model. There are also projects focusing on the impact of emotions on intelligent agents [35].

In summary, there are a great number of factors in CGF that are vague, incomplete and uncertain. Human beings often infer conclusions based on such uncertainty information. Therefore, it is necessary to develop tools for uncertainty reasoning in simulation engines, such as IPME, to support reasoning-related tasks, including situation awareness, decision-making, planning, and action in task network simulations within IPME.

III. Representing Uncertainty in Virtual Operators

LAMP (Language of Agents for Modelling Performance) is an approach of knowledge representation for various reasoning required by simulated task nodes in IPME [12], [36], or other task modelling tools. It is able to represent deterministic and uncertain knowledge and support similarity-based associative reasoning and rule-based abstract reasoning, interacting with IPME in real-time.

Fig. 1 is a conceptualization of LAMP (lower portion) interacting with a task network in IPME (upper portion). The communication between LAMP and IPME is through a TCP/IP (Transmission Control Protocol /Internet Protocol) socket interface. LAMP encompasses a *Reasoning Interface*, *Reasoning Engines* and *Aspect networks*. The *Reasoning Interface* module receives data from IPME, activates the reasoning system to get conclusions or solutions, and sends the results to IPME to affect task execution. The *Reasoning Engines* activate *Aspect networks* within LAMP and provide computational support to various reasoning methods, such as probability, fuzzy, propositional and analogical reasoning.

The *Aspect networks* are the knowledge base in LAMP, in which each *Aspect* is a knowledge unit with *InputInterface*, *ReasoningKnowledge*, *OutputInterface*, *LearningInterface* and *SocialInterface*. In the simulation process of IPME task networks, any simulated task node can communicate with LAMP's *Reasoning Interface* to activate the reasoning system, send requests to and get conclusions from the reasoning system, and then use the reasoning results for further task simulation. The following describes the details of main components in *Aspect*s.

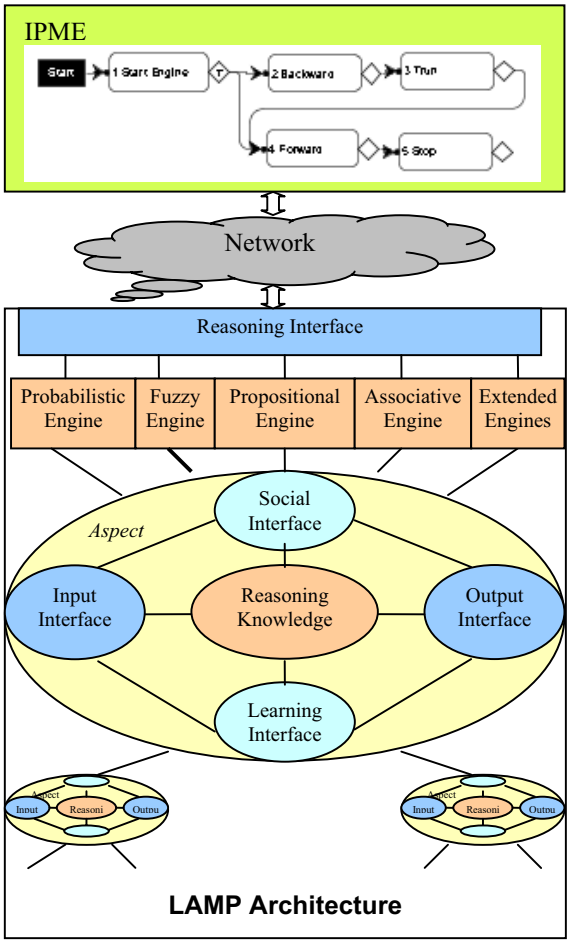


Fig. 1 Overview of LAMP and IPME

InputInterface holds data from the task simulation in IPME and converts the data into an internal representation. *OutputInterface* sends the reasoning results to the task simulation in an appropriate format. *LearningInterface* and

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SocialInterface are future components in LAMP to provide mechanisms for automated knowledge acquisition or interactions with other *Aspect*s.

At the core of *Aspect*, the *ReasoningKnowledge* defines a dual-process knowledge representation [37] [38] [39] [40] with abstract derivations and associative mappings. The abstract derivation process is certainty-related and rule-based system for probability, fuzzy and proposition inferencing. The associative mapping process is memory-based analogical model. Both the abstract and associative processes can interact to support hybrid reasoning.

ReasoningKnowledge is organized into *features*, *items*, *nexuses*, *traces* and *rules*. A *feature* is a pair of name-values, such as "*shape=circle*". An *item* represents a concept, object or fact with a group of *features*. For example, a *vehicle* is an item with features including "*maker*", "*model*" "*color*", etc. A *nexus* embodies a union of data *items, with a certainty and a set of features.* For instance, *"[Travel, UAV123, Toronto, NewYork]* represents a nexus named *"Travel"* that associates the vehicle *"UAV123",* the departure city *"Toronto"* and the destination city *"NewYork"*. A *trace* models an event or experience with groups of nexuses representing background, description, plans, solutions, etc.

A *rule* is a pair of conditions and actions in which each condition or action is a nexus. Rules correspond to abstract derivation knowledge for a variety of reasoning methods. Each rule may also contain meta-attributes for behaviour moderators or statistical data of reasoning performance. For example, each rule has a firing priority that can be used to affect precision and effectiveness of reasoning process. The following schema describes a rule:

Rule = <*Id*, *Type*, *Conditions*, *Actions*, *MetaAttributes*>,

where *Id* is the identifier of this rule; *Type* may be proposition, fuzzy, probability or analogy; *Conditions* consist of a group of nexuses as arguments, while *Actions* include outcomes of the rule; *MetaAttributes* characterize behaviour moderator effects or other meta-properties, for example, personality and emotion, that affect this rule's reaction features such as firing priority or response delay. An example of rule is as follows:

```
Rule = {   /* RPM: Revolutions Per Minute */
  Id = RotorRPMControlRule1;
  Type = fuzzy;
  Conditions  = ( [ RotorRPMChangeRate, Negative],
                  [RotorRPMError, Negative]
  Actions = ([RPMAdjustment, Positive])
  MetaAttributes = {FiringPriority = getRPMPatternPriority
                                (AnxietyDegree, Emotionality),
                    ResponseDelay = getRPMPatternResponseDelay
                                (AnxietyDegree)}
```

In this example, the reasoning *type* is *fuzzy*, using fuzzy logic to make a judgment, and the *Id* is *RotorRPMControlRule1*. There are two nexuses in the *Conditions*, *RotorRPMChangeRate* and *RotorRPMError*, each of which contains an item identifying relevant fuzzy set and a *certainty*. The *MetaAttributes* comprises two attributes (*FiringPriority* and *ResponseDelay)* that are computed through functions based on the current operator's personality traits including anxiety degree and emotionality, and used to affect the effectiveness and speed of this rule's reaction.

The reasoning system works with IPME to offer various reasoning required by simulated tasks. When an IPME task activates the reasoning system, the *InputInterface* receives associated data and queries from IPME. The reasoning system activates the corresponding reasoning engine and employs a related derivation mechanism to draw conclusions or solutions. Finally, the *OutputInterface* sends the solutions or conclusions as variable values back to the IPME task for further use.

IV. Supporting Military Applications

In this section, we describe an example for helicopter control with fuzzy reasoning. Typically, helicopter control is modelled as a task layer, such as "take off", "hover", "descend," "forward" and "backward", and a behaviour layer including "heading", "lateral", "longitude" and "altitude" controls. In order to perform a task, one or more behaviour functions have to be activated to make adjustment for the desired output. For example, for "hovering", pilots should look for small changes in the helicopter's lateral, longitudinal and height controls.

There are a variety of strategies to represent helicopter control, such as PID (Proportional-Integral-Derivative), fuzzy logic and neural networks [27]. PID control is a traditional and powerful method, but it is abstract and the parameter tuning can be time consuming. Neural networks can also be used for helicopter control, but it cannot explain its reasoning process and need more computation efforts affecting real-time applications. Fuzzy logic is a human-like approach and easier to relate to a pilot's description of control and has been found to be easy to tune.



Fig. 2 A photograph of a helicopter control panel and flight controls (left) with the corresponding representation in the simulator (right)

A helicopter simulator (as shown in Fig. 2) can be connected to IPME model of the pilot actions as shown in Fig. 3, adjusting the controls during a simulation. Fig. 4 is the Aspect structure for the reasoning used in the IPME task network. The piloting tasks invoke the corresponding Aspects

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to derive relevant control adjustments for heading, position, altitude controls, et cetera.

We describe the details of the *Aspect* "*InferLongitude*" in Fig. 4. Pitch angle change rate and pitch angle error are used to derive the adjustment amount of longitudinal cyclic. The allowable ranges of pitch angle change rate, pitch angle error and the longitudinal cyclic as conclusion are partitioned respectively by the following five fuzzy sets expressing the approximate nature of the measurements: "*VeryNegative*", "*Negative*", "*Zero*", "*Positive*", and "*VeryPositive"*.

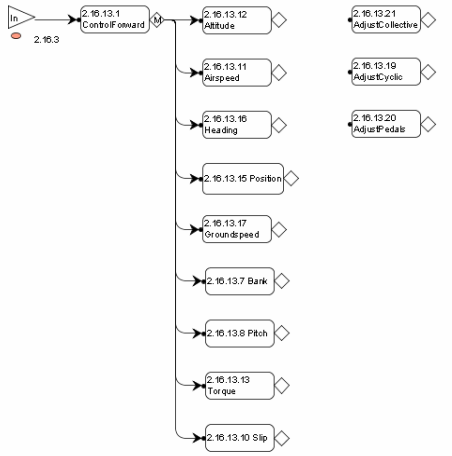


Fig. 3 A simplified IPME task network for the simulation of helicopter control

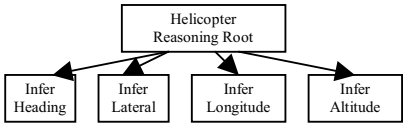


Fig. 4 The *Aspect* structure for the simulation of helicopter control

The fuzzy membership functions for the longitudinal cyclic control are shown in Fig. 5, where the longitudinal cyclic *L* is output and the pitch angle change rate *R* and the pitch angle error *E* are inputs. The dependence relationships between longitudinal cyclic and pitch angle change rate and pitch angle error are shown in Fig. 6, which form the *Conditions* and *Actions* in fuzzy rules. For example, in the Fig. 6, if the RPM change rate is *Negative (denoted as N)*, and the RPM error is *Negative (N)*, then the current RPM adjustment should be *Positive (P)*.

When the IPME task that controls position invokes the reasoning system to correct an error in the lateral position, the fuzzy reasoning engine asks IPME for situation data including "*SetPoint*", "*CurrentPitchAngle*" and "*LastPitchAngle*". It, then, derives the longitudinal cyclic change through rules and fuzzy computing. Finally, it returns the derived adjustment amount to IPME where it is applied to the helicopter simulation controls in a repeating process.

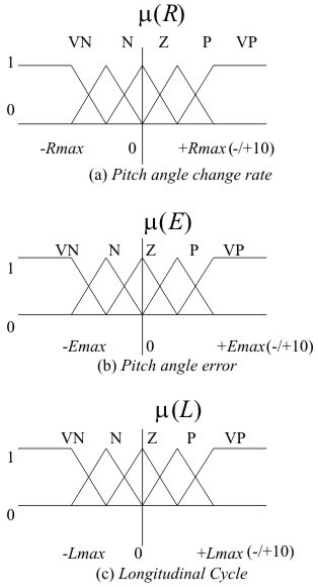


Fig. 5 Membership functions for pitch angle change rate, pitch angle error and longitudinal cyclic

RPM Error \ RPM Change Rate	*VN*	*N*	*Z*	*P*	*VP*
VN	*VP*	*VP*	*P*	*P*	*Z*
N	*VP*	*P*	*P*	*Z*	*N*
Z	*P*	*P*	*Z*	*N*	*N*
P	*P*	*Z*	*N*	*N*	*VN*
VP	*Z*	*N*	*N*	*VN*	*VN*

Fig. 6 Longitudinal cyclic adjustment based on pitch angle change rate and pitch angle error

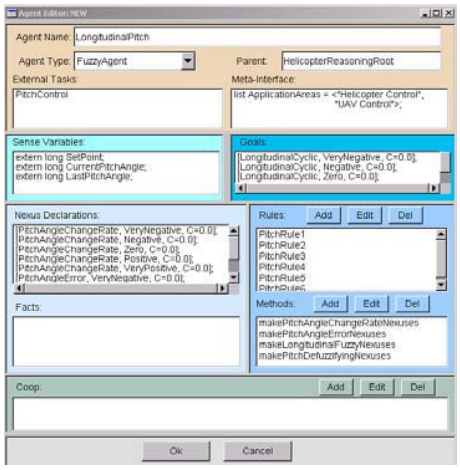


Fig. 7 Attributes of the Aspect for longitudinal position control

Fig. 7 is a screen shot of the corresponding *Aspect* that consists of 25 rules related to the relationships in Fig. 6 and four methods for data conversion between sense data and nexuses in rules. Fig. 8 shows an example of the resulting fuzzy conclusions. When *SetPoint* is *0.0*, *CurrentPitchAngle* is *–3.0* degrees and *LastPitchAngle* is –7.0 degrees, the

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reasoning result is "[*NumericLongitudinalCyclic, -3.846154, C=1.000000*], i.e. in this case, the adjustment of the longitudinal cyclic is minus *3.846154* degrees.

Fig. 9 shows the comparison between fuzzy control and a PID control for longitudinal-pitch control (initial pitch angle: –7.0; set point: 0.0). We found that the fuzzy control curve is smoother, while the PID control contains more oscillations for similar development time, although further tuning should improve the PID controller.

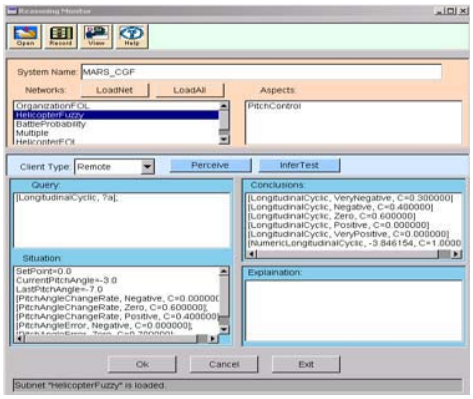


Fig. 8 Reasoning results of the request "LongitudinalPitch"

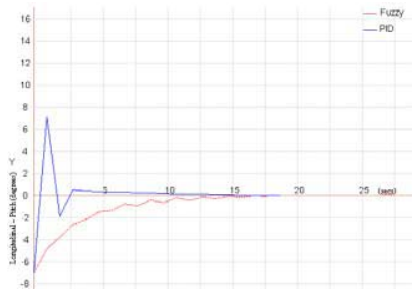


Fig. 9 Result Comparison between fuzzy control and PID control

V. Conclusions

Compared to other approaches, LAMP's distinctions lie in (1) being able to interact with the simulation engine IPME in real-time for continuous reasoning in simulated tasks to represent human behaviour, (2) supporting dual-process reasoning including abstract-level deriving and association-level searching and analogical mapping, (3) providing multiple reasoning methods for both deterministic and uncertainty inference, and (4) modelling the impacts of behaviour moderators in variable levels.

A number of tentative conclusions and limitations can be drawn based on the results in this study. These results have also raised issues that may benefit from additional research.

A literature review and analysis about uncertainty in military applications indicated that it is often difficult to get deterministic data and models for many military simulation areas. In order to support better reasoning and decision-making in CGF, current simulation engines, such as IPME, should be extended with advanced reasoning mechanisms to support uncertainty in military simulation and modelling.

The current implementation of LAMP indicated that it is possible to integrate multiple uncertainty reasoning approaches for various simulated tasks under a unified architecture. At the moment, this system deals with proposition, fuzzy and probability methods at the abstract level, and the analogy reasoning at the associative level. Furthermore, LAMP has the capability to integrate new approaches.

With the examples developed in the current system, this study provided indication that the reasoning system has the potential to be used in different military simulation areas. At present, examples are involved in command and control, helicopter control, and personnel relationship reasoning in an organization.

The current studies also raised many important issues that should be considered in future research, including exploring the automatic selection of reasoning methods; refining the support to behavior moderator modelling, and developing HLA compatible interface; and making more efforts on the validation of integration mechanism.

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