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On the Modeling and Construction of an Artificial Landing Safety Officer (LSO) for Conducting Pilot Training in a Helicopter Deck Landing Simulator

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Abstract - *Using concepts and techniques from User Modeling, Fuzzy Logic and Intelligent Agents, a Self-Adaptive Landing Signals Agent (SALSA) was developed at the Royal Military College of Canada for integration in the helicopter simulation and training facility of The Defense Research and Development Canada (DRDC) centre in Toronto. In the context of this work, self-adaptive means the ability to assess the skill level of the pilot, the ship motion and the environmental conditions inside the simulator, and adapt its behavior accordingly, just as a human landing safety officer (LSO) would. Furthermore, SALSA can recall its last assessment of a pilot it has worked with, or quickly make an estimate of the skills of a new pilot, and use that information to commence training at the appropriate skill level. Preliminary tests indicate that SALSA is able to simulate a human LSO and assist in providing progressive training in the simulator.*

Keywords: Intelligent agent, fuzzy logic, modeling and simulation.

1. Introduction

The training environment discussed consists of a navy ship, a helicopter with a pilot and a landing safety officer (LSO) on board a ship. To land a helicopter on board could be a very tough task when the sea states are rough. Normally, the cost to train a pilot to land in this environment is very expensive; see Figure 1 for the training environment in real life. Alternatives using modeling and simulation were investigated.

The Defense Research and Development Canada (DRDC) centre in Toronto has developed a virtual reality simulator to conduct training for Sea King helicopter operations aboard a Canadian Forces patrol frigate. In the present simulator configuration, a "Human Landing Safety Officer" LSO is required to conduct a realistic simulation involving all phases (approach to landing) of the helicopter.

Figure 1. Shipboard Helicopter Operations[1]

Using concepts and techniques from User Modeling, Fuzzy Logic and Intelligent Agents, a Self-Adaptive Landing Safety Agent (SALSA) was developed at the Royal Military College of Canada for the integration in the helicopter simulation and training facility of DRDC. Preliminary tests indicate that SALSA is able to simulate a human LSO and assist in providing progressive training in the simulator.

2. A Self-Adaptive Landing Signals Officer

Training a pilot, who can perform deck landing, needs a lot of resources and people, such as the ship, helicopters, and pilots, LSOs. It is natural to take an alternative of using modeling and simulation to fulfill the task. We participate in a design of helicopter deck landing system to make deck landings in Sea Kings aboard a Canadian Patrol Frigate in severe weather conditions. Our task is to design an agent to replace the role of a human LSO. The LSO is usually himself a Sea King Pilot so that the cost of carrying out a full simulation is greatly increased by the need of such an individual. Hence the requirement to investigate the possibility of replacing the LSO by an intelligent agent with similar characteristics as it's human counterpart.

For a pilot, based on the communication between hiself and the human LSO, the pilot attempts to match the postion and velocity of the helicopter to the traps positon and velocity. While the LSO has a better view to the relevant position between the helicopter and the trap, and most importantly, an LSO can feel the rolls and pitches of the ship movement. An LSO will sit in a small room in the corner on the landing deck, and he will feel the rolls and pitches of the ship, watch a helicopter approaching the deck, and give command directly to the pilots when the helicopter tries to fly over the trap in the center of the deck in order to safely land on the deck eventually, see Figure 2.

Figure 2. Rapid Assist Securing and Traversing System (The Trap)[2]

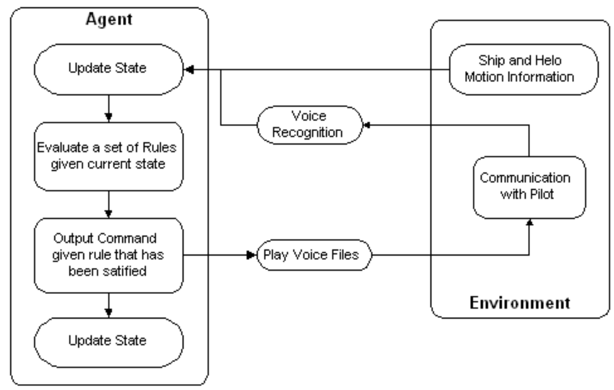
The design of an intelligent agent based LSO were fulfilled in three phases. Firstly, the architecture of an intelligent agent system was planned. Secondly, a constructive LSO was built using fuzzy logic. Thirdly, a self-adaptive LSO was designed and tested. In the context of this work, self-adaptive means the ability to assess the skill level of the pilot, the ship motion and the environmental conditions inside the simulator, and adapt its behavior accordingly, just as a human LSO would.

3. The System Architecture of an Intelligent Agent Based LSO

An agent is anything that perceives its environment through sensors and acts upon that environment through effectors[3][4].

Figure 3 below illustrates the Constructive LSO Architecture.

The prototype agent provided orders that guided an experienced pilot to a successful landing under a specified set of environmental conditions. The success of the prototype[2] agent does depend upon manually finding and setting the right set of parameters for that pilot in those conditions. But it is recognized that the prototype LSO agent lacked the ability to adapt itself to environmental conditions or pilot expertise as a human would. Further, the prototype agent was designed only for the final landing phase, the most complex part. In order to replace the functions of a human LSO, an AI system must also be able guide the pilot through all four phases of the landing sequence, transitioning between



them properly.

Figure 3. the Constructive LSO Architecture

4. SALSA

The goal of building SALSA is to research and develop a means to expand the prototype LSO AI agent discussed above so that it can imitate the abilities of a human LSO to judge and adjust to pilot expertise and environmental conditions through all four phases of a free deck landing in a simulator.

SALSA continues to decide which commands to issue and when. It is, in effect, be an agent within a larger agent. The larger agent includes a controller strategy module. This module uses the current version of the user model and the current picture of the sea state to decide the best approach to land a pilot of this skill level in this weather. The "best approach" will exist as a set of parameters that are transferred to the command issuing agent to guide it in its function. The controller strategy module can also consult a domain expert database. This database contains information, such as safety limits, which represents the current Canadian Forces standards for landings aboard ships. Should these standards change, only this database need be modified instead of searching the programs for the appropriate values. The environment and pilot assessment are completed using two other fuzzy inference systems (FISs), which take data from the simulator as input. These assessments are used by the user modeling bureaucracy modules, which are responsible for creating, updating and storing the current user model as well as feeding it to the strategy module after each update. The conceptual architecture is shown in Figure 4.

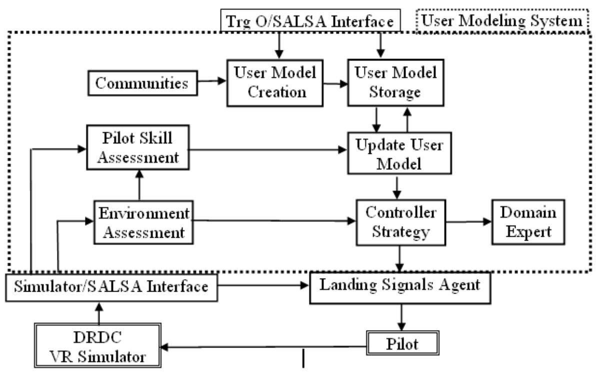


Figure 4. SALSA Conceptual Architecture

Following sections shows more detailed techniques to build SALSA.

5. Fuzzy Logic and User Modeling

Fuzzy logic[3] offers many advantages to SALSA. In the control aspect of the problem—where SALSA must decide when to issue commands and which commands to issue based upon the motions of the ship and helicopter—it is difficult to assess the physical parameters associated with the problem. This creates uncertainty. It is also difficult to assess the sea state in which the pilot is flying. DRDC's simulator tries to imitate real conditions, causing some of the uncertainty found in judging real weather. Third, the simulator is used by a human pilot. Guiding that pilot and assessing his skill involve uncertainty because of the inherent vagueness and uncertainty in humans. Lastly, the goal is to generate output that simulates a human LSO. That means imitating the same inherent human vagueness and uncertainty in the agent's decision-making and output to the pilot. Fuzzy logic is well-suited to dealing with vagueness and uncertainty.

5.1 The Environment Is Fully Accessible To an Agent Based LSO

Because the LSO agent could access to the complete states of the environment through the helicopter landing simulation system, we claims that the environment of the LSO is fully accessible. The list of information needed for an LSO to make decision could be found from Table 1.

Table 1. Four types of data required for the constructive LSO.

	Four types of data required
1.	The position and orientation data of the ship that the helicopter is trying to land on.
2.	The helicopter dynamics data.
3.	Pilot landing procedure.
4.	Pilot training information.

5.2 User Modeling (UM)

One extra piece of information might be useful: the performance of the pilot during landing. That means even though a pilot was well trained, but he/she might not perform as one expects. In this case, this piece of information will not directly from the simulator. The constructive LSO must be able to identify the abnormality, and change it strategy accordingly. Here, we use the concept user modeling [5][6].

"When a computer customizes its behavior for individuals, it is said to be *modeling* its users. The study of how best to accomplish this feat is called user modeling." [5]

The original academic work of UM was primarily concerned with modeling the *cognitive* characteristics of the user while the commercial research is concerned primarily with *behavioral* characteristics (what has he done, what is he doing, how does he prefer to do it)[6]. The focus of this work, an agent responding in real time to the behavior of a human pilot, suggested that the methods developed for the behavioral approach would be more appropriate.

In UM, there are two broad categories of knowledge acquisition: invasive and passive. *Invasive* means that the UM system directly asks the user for input or directly offers him alternatives to choose from. The most important problem with invasive measures for this research is that the user of the Sea King simulator has no means of answering invasive questions during the simulation. The VR simulator contains the standard controls found in a helicopter, not a computer screen or keyboard. Invasive questions could only be answered before or after the simulation. However, prior to any user entering the simulator, SALSA will require the training officer to log the user in. If it is a user's first simulation, SALSA will invasively question the human training officer to obtain the user's identifying information and a general assessment of the user's skill level. SALSA has no other invasive knowledge acquisition measures[2].

Passive acquisition of knowledge about the user relies on observing his behavior. These observations are used to infer knowledge about the user. In SALSA, this is accomplished by monitoring the data from the simulator and using the fuzzy inference systems. The advantages of passive techniques are that they don't bother the user, they can collect information in many different ways and can be collected continuously for continuous updating of the model[5]. The disadvantage is that all information from them must be inferred. And that inference is only as accurate as the algorithms that do the inferring and the knowledge or prejudices of the programmers that wrote them.

5.3 The Fuzzy Inference System

The behaviors of the adaptive constructive LSO are based on a real human LSO's behaviors. For example, we could describe a level of pilot training by using a rough scale, say from 1 to 5, 1 would represent novice level without any experience on deck landing, and 5 fir an expert level with years of landing experience on board a ship.

To build such a system as a constructive LSO, we interviewed pilots with various landing experiences, who also play role of LSO as part of their training process. To convert these verbal and blurred descriptions of the behaviors of an LSO to a precise representation into a simulator, a Fuzzy Logic inference system should be used. Figure 4 shows the basic structure of this system, which just uses three pieces of information: the training level of a pilot, the performance of a specific pilot at the moment of landing, and the relative positional and speed information of the ship and the helicopter.

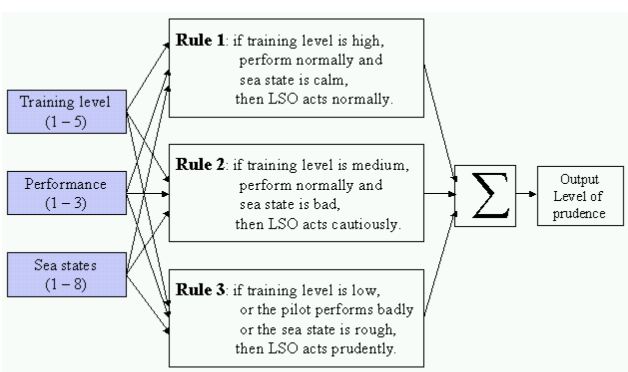


Figure 5. The basic structure of the fuzzy inference system.

Figure 5 shows that the fuzzy inference system uses three pieces of information: the training level of a pilot, the performance of a specific pilot at the moment of landing, and the relative positional and speed information of the ship and the helicopter

5.3 Special considerations for the performance factor

In a rough sea state, to keep a low relative speed between the trap and the helicopter, to keep the probe close to the trap is very hard, even for an experience pilot. So it is necessary for the adaptive LSO to watch the performance of the pilot in landing. It is also crucial to watch the final landing phrase, which is called Low Hover landing, meaning: helicopter over the trap and altitude is about 4 feet above deck.

What an LSO could percept from the helicopter landing simulator are Current Time, Helicopter Heading, Helicopter Position (x,y,z), Trap Position (x,y,z), Helicopter Velocity (x,y,z), Trap Velocity (x,y,z), Ship Heading, Ship Pitch, Ship Roll, Ship Pitch Velocity, Ship Roll Velocity, and Voice Commands. By receiving these pieces of information for a short period of time, the constructive LSO will build an understanding about the quality the landing. Figure 6 shows the x positions of the pilots over time and compare them to his target position. They clearly show that Pilot 1 has more experience than Pilot 2. In a simulated environment, it is possible to make the landing condition identical, so the comparison could be precise.

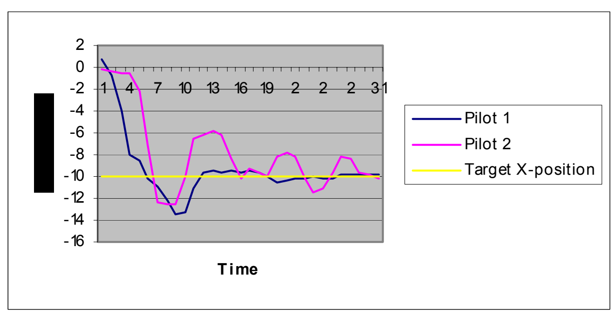


Figure 6. This figure plots the pilot x positions over time and compare them to his target position.

From Figure 6, we could also be able to image how to adjust the strategy for an adaptive constructive LSO. For example, a wider range of membership function could be given to Pilot 2, see Figure 7[1].

Wider "Ontop" will allow the adaptive constructive LSO issue a command more cautiously, and specifically the final landing command before the pilot could fly right over the trap. So the LSO could give command even the helicopter's probe is not right over the trap, a "land, down, down, down" command could be issued to avoid an unnecessary longer period of landing procedure.

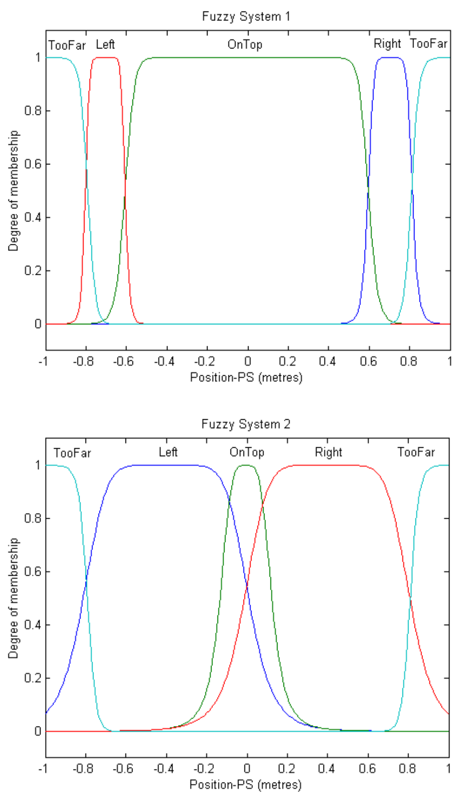


Figure 7. Different membership function will be given based on the adaptive LSO's understanding of the performance of a landing from a pilot.

Other techniques of UM are explored, for example, Stereotypes, Communities, and storage of the individual user models as files[2].

6. Evaluation, Testing and Discussion

To test our LSO systems, we need DRDC Toronto's deck landing simulation and many human pilots. This is an expensive operation. To be able to test our LSO systems, we started with build-in-house simulation test bed to check the concepts of our system design, and human pilot test at DRDC Toronto.

6.1 Testing the Constructive LSO

For the constructive LSO, the testing configuration utilized at DRDC Toronto consisted of the simulator, pilot, instructor 's console (used to control the simulator), computer with the LSO agent and a serial data connection between the simulator and computer. Commands generated by the LSO agent were read from the computer screen and passed to the pilot via headset.

An experienced Sea King pilot was employed to conduct the testing. Approximately 5 seconds before the pilot was anticipating ready to land the data recording was started. When the Ready to Land command was given by the pilot the start time would be recorded and the LSO agent was engaged to begin generating commands. The run was finished when the pilot landed or a decision was made to terminate in mid flight after several attempts to land were unsuccessful and it appeared the run was producing no new information. At the end of each run the data recorded was saved for post analysis. Originally it was envisioned that several runs form both port and starboard involving different types of ships motion small, medium, and large between 0 and 10 degrees could be conducted. Testing did not progress as quickly as anticipated resulting in all but one run being conducted with a very small deck motion around zero degrees. The last run, Run 11, was conducted with medium motion between 0 and 7 degrees. The total number of recorded runs was 11.

To assess performance of the LSO agent, feedback from the pilot and data analysis are utilized. The data collected during 11 different runs contains 71 occasions when the helicopter was considered over the trap. An occasion over the trap is defined as any time the flight path of the probe enters a 0.9 x 0.9 metre square by 2 m high box over the trap. The frequency distribution of average flight time over the trap indicates that 42 out of the 71 occasions have an average flight time over the trap greater than 1.5 seconds and 26 of 71 occasions have an average flight time over the trap greater than 2.5 seconds. Figure 8 shows the statistics.

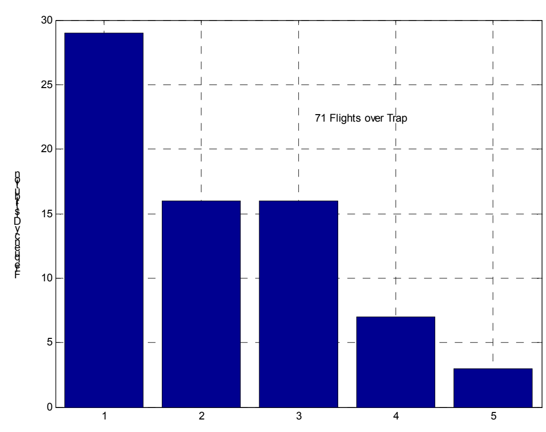


Figure 8. Frequency Distribution of Time Over Trap[1]

There are 32 occasions where the time spent over the trap is greater than 2 secs. None of these has an average velocity over the trap greater than 1 m/s. The relationship between the time over the trap, average velocity and the distance across the trap is represented by the two inverse curves one for a distance of 1.8 metres across the trap the other for 2.5 metres across the diagonal. These lines depict the dimensions in terms of velocity and time for a direct flight over the trap.

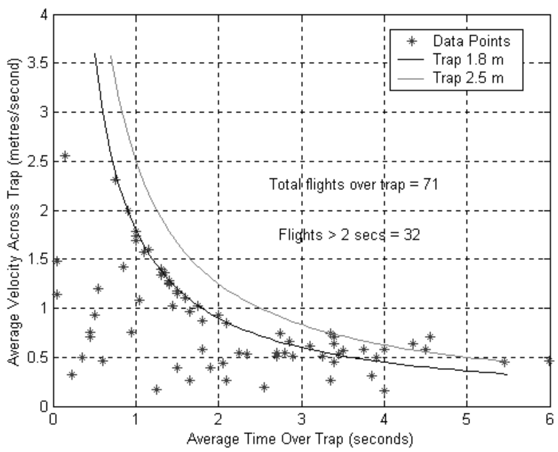


Figure 9. Average Velocity versus Time Over Trap[1]

An opportunity to land is an occasion over the trap where the flight path conditions are considered acceptable or almost acceptable for the LSO to give the Land command. It is defined as those 41 occasions over the trap having an average flight time greater than 1 second and an average velocity less than 1 m/s. Each opportunity to land is referenced by the run it occurred in and its sequence. For example Run 3 Opportunity 2 or the abbreviated form is Run 3 Opportunity 2.

Observations by the pilot suggested that the land command was not being generated as often as he was anticipating. If it can be demonstrated that the LSO agent is capable of generating more land commands by changing its configuration, then it can be concluded that the LSO can be effectively adjusted to accommodate the different flight profiles that were presented during testing.

6.2 SALSA Testing

The evaluation and testing of SALSA was completed incrementally, testing the programs written for each phase prior to moving onto the development of the next phase. Due to the unavailability of pilots and DRDC Toronto's simulator, simulations are developed in order to test and evaluate the SALSA programs. Some positive results are generated[2].

Although, in most cases, SALSA's output accuracy was very good to excellent. So, in terms of "number accuracy" SALSA correctly interprets what it sees and creates good results, for the most part. The question of accuracy and appropriateness remains partially unanswered for SALSA due to the lack of data[2].

7. Conclusions and Further Work

Two immediate future work must be conducted. First of all, more human pilots are needed for further tests of both the constructive LSO and SALSA. Second, more effective simulation method must be developed in the absence of human pilots and the helicopter deck landing simulator.

8. Acknowledgements

Special thanks to DRDC Toronto's support to the RMC's the LSO project. We would also like acknowledge the participation of Steve Gregg and Darrel Duckworth during different phases of the design and analysis.

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