Data informed cognitive modelling of offshore emergency egress behaviour

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Abstract

This paper applies a cognitive modelling approach to model decision making of naïve subjects in virtual emergency situations. Virtual environments (VE) can be used as a virtual laboratory to investigate human behaviour in simulated emergency conditions. Cognitive modelling methodology and human performance data from VEs can be used to identify the problem solving strategies and decision making processes of general personnel in offshore emergency egress situations. This paper demonstrates the utility of decision trees as a cognitive tool for two main purposes: 1) assessing VE training curriculum and 2) predicting human behaviour. To show these capabilities, the results of two empirical studies are compared using a decision tree induction approach. The first experiment investigated the learning and inference process of participants trained using a lecture based teaching (LBT) approach. The second experiment used another pedagogical approach – simulation-based mastery learning (SBML). Overall, decision trees were found to be a useful method for evaluating the efficacy of VE training, and as a basis for predicting individuals' decision-making performance.

Keywords: decision trees; decision making in emergencies; virtual environments; offshore emergency egress; training efficacy

Introduction

Offshore oil and gas platforms operate in remote and harsh maritime environments. As a result, offshore emergencies are complex, dynamic, and high-risk situations. Personnel responding to these emergencies are faced with uncertainty in managing the situation, and major time pressure in safely evacuating the platform. Decision making in high-stress emergency situations can vary from person to person. This variability could be a result, in part, of conventional training in which people tend to employ different learning strategies and develop their understanding of emergency protocols differently (Musharraf et al., 2016). However, individual differences and unpredictable responses to emergency situations can undermine the emergency response operations. Therefore, effective training in emergency response and preparedness is critical for ensuring offshore safety.

Virtual environments (VE) can address existing training gaps and augment conventional offshore safety training by providing artificial experience that would otherwise be too dangerous to practice (Smith et al., 2017). VE technology can allow offshore operators to familiarize personnel with the worksite and to practice emergency exercises before going offshore. However, verification of the VE training curriculum is required to confirm it meets the intended training purposes.

Cognitive modelling methodology can be used to inform the quality of VE training. Developing a cognitive model of human behaviour in these virtual emergency situations can provide valuable insight with regards to improving offshore safety systems and training programs. The VE allows researchers to observe how humans use information to accomplish specific tasks (Musharraf et al., 2016; Roth et al., 1992). Cognitive modelling methodology and human performance data from virtual environments can be used to identify the problem solving strategies and decision making process (e.g. model the knowledge base and inference process) of personnel in offshore emergency situations.

This paper demonstrates the use of a cognitive modelling methodology – decision trees – to evaluate the efficacy of VE training. This approach was introduced by Musharraf et al. (2016) and is based on two experimental studies that investigated the effectiveness of VE training curriculum on competence. The model focuses on the decision making process of naïve subjects in virtual emergency situations, particularly the participants' route selection strategies. The first experiment involved lecture-based teaching (LBT). Participants in the experiment showed variability in responding to emergency situations. The variability manifested itself in many different decision strategies. To address this variability and to improve learning outcomes, a second experiment was designed, which employed a different pedagogical approach called simulation-based mastery learning (SBML) (McGaghie et al., 2014). Subsequently, the in-simulation performance of participants from both studies was compared using decision trees.

The paper describes the theoretical framework, data collection process, and how the knowledge bases were created. Further, it explains the algorithm that runs the inference engine to produce the decision trees. A process for testing the prediction accuracy of the decision trees is also described.

Theoretical Background

Cognitive Functions

Four major cognitive functions are performed by personnel in emergency egress situations: perception, interpretation, decision making, and execution. For example, in an emergency, personnel hear an alarm and are required to muster at their designated muster or lifeboat stations by following a safe egress route. These cognitive functions are repeated based on the personnel's situational awareness and whether they encounter hazards or obstructed routes.

- Perception – perceive audio-visual cues from the environment.
- Interpretation – analyze the perceived cues and infer what the alarm and public address (PA) mean (i.e. which route is obstructed, where to muster).
- Decision Making – assess different potential egress routes and choose the safest path.
- Execution – follow egress route until designated muster or lifeboat station is reached.

Learning and Inference

This paper investigates how people develop and use different problem solving strategies, specifically route choices, given their VE training. This is modeled by a knowledge base and an inference engine. In the model, all the knowledge gained from training and experience in the VE is stored in a knowledge base. The content of the knowledge base is then used by the inference engine to develop a human reasoning structure. Figure 1 shows the inference process.

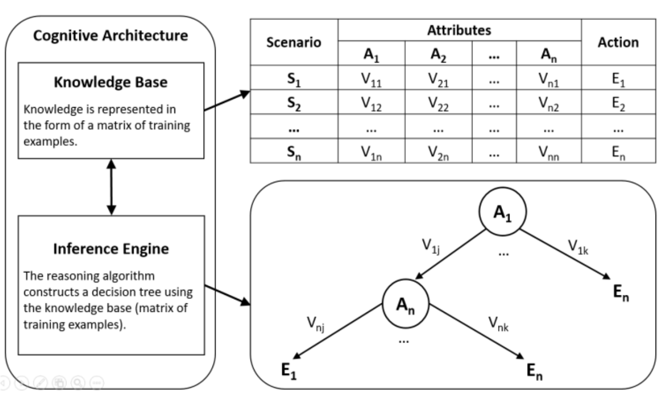


Figure 1: Knowledge Base and Inference Engine

Knowledge in the knowledge base is represented using a matrix of training examples. Scenarios are represented by S_1, S_2,…, S_n. Attributes of the scenario are represented by A_1, A_2,…, A_n. Actions taken are represented by E_1, E_2,…, E_n. The values of the attributes are represented by V_{ij}, where the value represents the j^{th} value of the i^{th} attribute. The knowledge matrix is used by the inference engine to construct a reasoning algorithm. An inductive reasoning approach – decision tree – was used in this paper. Decision trees were selected based on their visual simplicity and diagnostic capabilities. Decision trees can be constructed relatively quickly compared to other methods, such as artificial neural networks, or support vector machines (Duffy, 2009). Another benefit is that they do not require any prior assumptions about the data.

Decision Tree Induction

The goal of the decision tree induction is to classify the content in the knowledge base into groups such that the data set in each group belongs to the same class (Badino, 2004). The classification is performed based on the value of selected attributes. Several attribute selection measures are available, including *information gain, gain ratio, and Gini index*. This paper uses the ID3 decision tree algorithm, which uses information gain as an attribute selection measure (Han et al., 2011). Information gain is calculated using the idea of entropy. Given the entropy of a data set *S*, information gain of an attribute *A* can be calculated using equation 1.

$$Gain\ (A) = Entropy\ (S) - Entropy\ (A) \qquad (1)$$

Here, *Entropy(A)* presents the weighted average uncertainty of the groups created by classifying the data set using attributes (A_i). Details of entropy calculation can be found in Han et al. (2011). The decision tree algorithm takes two basic inputs: the data set in the knowledge base and the list of scenario attributes. During the decision tree induction, data are iteratively classified using the attribute that has the highest information gain, as highest gain refers to lowest uncertainty. The following steps are repeated until no attributes are left for classification, or the data set is empty, or data in each group belong to the same class and no further classification is needed.

Step 1: For each attribute A_i, compute the value of information gain $Gain(A_i)$.

Step 2: Choose the attribute with the highest gain $Gain(A_i)$ and classify remaining data set based on A_i.

More details on the decision tree algorithm can be found in Musharraf et al. (2016).

Experimental Methodology

Two experiments were conducted: the first focused on conventional LBT methodology and the second focused on SBML. Both studies used a VE called the All-hands Virtual Emergency Response Trainer (AVERT). This section will describe the training, data collection in AVERT, formation of the knowledge base, and resulting decision trees.

AVERT Simulator

AVERT is a first person perspective VE that was developed to train basic offshore safety practices to general personnel –

individuals whose responsibility in an emergency is to muster at their designated muster stations (House et al., 2014). AVERT scenarios involve basic wayfinding, alarm drills, and emergency response exercises. AVERT delivers training scenarios, tracks in-simulation performance metrics, and provides corrective feedback.

LBT was used to train 36 participants in how to successfully muster during offshore emergency situations in the VE. Participants attended three separate sessions. Each session involved a computer based training tutorial, followed by four training scenarios, and four testing scenarios in AVERT. The content of the tutorials included basic offshore emergency preparedness, alarm recognition and assessing the emergency situation, and hazard avoidance. Participants only received one exposure to each scenario and were provided minimal feedback on their performance. Details of the study can be found in (Smith et al., 2015). Data from 17 of the participants (13 male and 4 female, with a mean age of 26.8 years, standard deviation of 5.0 years) were used in this paper for comparison to the SBML approach.

SBML was used to train 55 participants in offshore emergency egress using the VE. This pedagogical approach was used to ensure that participants acquired and demonstrated the knowledge and skills necessary before advancing to more complex emergency situations. SBML involved a series of four training modules. Each module was designed to train specific learning objectives and gradually taught participants the platform layout, how to recognize alarms, what to do in the event of blocked routes, as well as how to assess the situation and avoid hazards while evacuating the platform. As part of the SBML training, participants were required to achieve demonstrated competence in all training and testing scenarios. The participants were tested repeatedly on their competence over the course of the training modules. They received detailed feedback on their performance after each attempt of a scenario. To achieve demonstrated competence, some participants required multiple attempts at the scenarios. Details of the study can be found in (Smith et al., 2017). Data from 15 randomly selected participants (12 male and 3 female, with a mean age of 25.6 years, standard deviation of 8.0 years) were used for comparison.

Data Collection and Modelling

Two training modules were the focus of the decision tree analysis: the ‘Alarm Recognition’ and ‘Assessing Situation’ modules. In both the LBT and SBML approaches, participants had to perform in twelve scenarios. The training scenarios differed between the training approaches as the SBML training provided more in-simulation instruction and feedback. However, the testing scenarios were the same for both training approaches. A subset of scenarios was used to populate the knowledge base (8 and 9 scenarios for the LBT and SBML training, respectively). Half of the scenarios were used to generate the knowledge base for the ‘Alarm Recognition’ module (denoted KB1) and the remaining scenarios were added to the knowledge base for the ‘Assess Situation’ module (denoted KB2). Two test scenarios were used to test the prediction capabilities of the decision trees (scenarios T1 and T2).

Knowledge Matrix Following rule based methodology, a knowledge matrix was created using the data from the participant’s performance in the training scenarios. Data to populate the knowledge matrix was collected from the AVERT report files generated for each scenario and from observations logged in-situ. Table 1 lists the attributes varied for each scenario and their possible values.

Table 1: Possible values for each attribute.

Attribute	Possible Values
Final destination	Muster, Lifeboat
Alarm type	None, GPA, PAPA
Hazard presence	No, Yes
Route directed by PA	None, 1st, 2nd
Obstructed route	None, 1st, 2nd
Previous route selected	1st, 2nd

Scenario Frames Participants were required to complete a series of scenarios of varying complexity. Basic scenarios involved participants practicing their egress routes and muster procedures. More complex emergency scenarios were dynamic in the sense that the value of some attributes changed during the scenarios. To capture the dynamic aspect, these scenarios were split into two or more frames. Figure 2 shows an example of two frames for a training scenario (S9) and how the knowledge matrix is updated based on the change in attributes of the scenario.

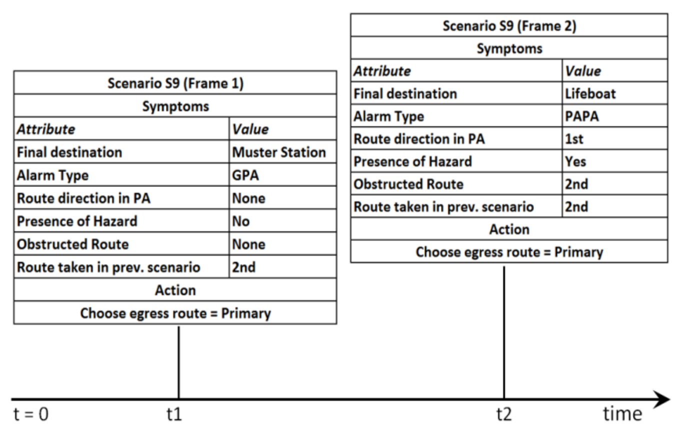


Figure 2: Example of scenario frames F1 and F2 for S9.

Table 2 shows the state of the knowledge base for a sample participant in the SBML program after finishing all training modules. Each row in the knowledge base contains the values of different attributes for the scenario and the corresponding action. For both studies, the participants’ perceived scenario attributes and corresponding actions for

Table 2: Knowledge matrix for alarm recognition (KB1) and assessment emergency (KB1 and KB2) training modules.

Category	Scenario	Attributes						Actions
		End Point	Alarm	Route by PA	Hazard	Blocked Route	Previous Route	
KB1	S1	Muster	None	1st	No	None	N/A	Primary
	S2 (F1)	Lifeboat	None	1st	No	None	1st	Primary
	S2 (F2)	Muster	None	2nd	No	None	1st	Secondary
	S3	Lifeboat	None	None	No	None	2nd	Primary
	S4	Muster	GPA	None	No	None	1st	Primary
	S5	Muster	GPA	None	No	None	1st	Primary
Test 1	T1	Muster	GPA	1st	No	None	1st	Primary
KB2	S6	Lifeboat	PAPA	1st	No	2nd	1st	Primary
	S7	Lifeboat	PAPA	2nd	Yes	1st	1st	Secondary
	S8	Lifeboat	GPA	2nd	Yes	1st	2nd	Secondary
	S9 (F1)	Muster	GPA	1st	Yes	2nd	2nd	Primary
	S9 (F2)	Lifeboat	PAPA	1st	Yes	2nd	2nd	Primary

each scenario were included as entries in the knowledge base. Because the SBML training required participants to reattempt scenarios until they correctly completed the task, only successful route strategies were stored as entries in the knowledge matrix.

Decision Trees Decision trees visualize how participants formed decisions based on the knowledge matrix. Decision trees also provide insights on what attributes had the biggest impact on participants' decision making. Figure 3 shows a decision tree based on the knowledge matrix in Table 2.

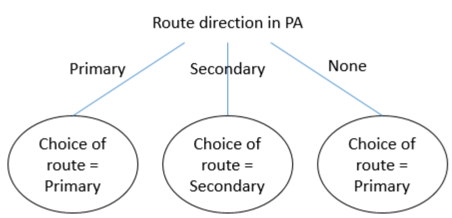


Figure 3: Decision tree developed after KB1.

In this case, the participant's route selection was decided based on their understanding of the information from the PA announcement. If the PA directed them to a safe route, then the participant took that route. If the PA did not provide any information regarding the safety of the route options, then the participant's choice defaulted to their primary egress route. The tree can subsequently be used to predict participants' choice of route (i.e. primary or secondary) for a given future scenario.

Results

For presentation purposes, the participants' decision trees after module 2 and 4 ('Alarm Recognition' and 'Assess the Situation') of the SBML experiment were developed to see how the trees evolved as more training content was added to the knowledge base. The different decision trees are summarized in Table 3. The detailed decision trees for the LBT experiment can be found in Musharraf et al. (2016).

Comparing the Alarm Recognition Decision Tree

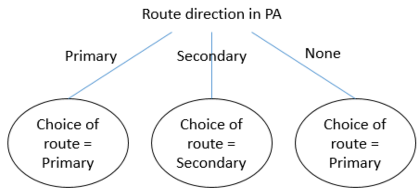
In an emergency situation, the alarm type dictates the final muster location. The main learning objective for this module was for participants to listen to the alarm and the PA announcement and take the safest route available in response to the situation. A decision tree for this situation is depicted in Figure 3. Eighty percent of participants in the SBML study developed the decision tree depicted in Figure 3 before the test scenario (T1). Forty one percent of participants in the LBT study had the same decision tree. Twenty percent of SBML and 24% of LBT participants based their route decision on alarm type or end point when the PA did not provide any route information. In this case, the participants interpreted that the general platform alarm (GPA) meant taking the primary route, and that the prepare to abandon platform alarm (PAPA) meant taking the secondary route.

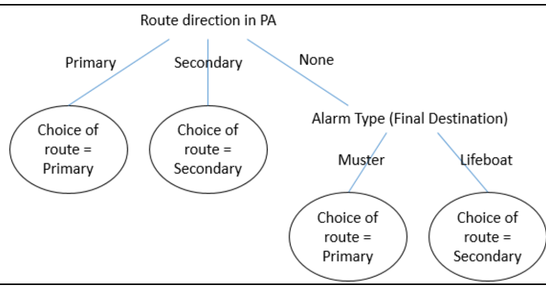
Comparing the Assess Emergency Situation Tree

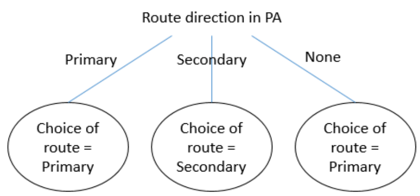
In an emergency situation, it is critical that personnel listen to the PA announcement, continually assess their surroundings, and follow the safest egress route available. If personnel encounter an obstructed route, they must re-route in response to the hazardous situation. Building on earlier learning objectives, the 'Assess the Situation' module trained participants how to assess the emergency situation, avoid hazards, and follow the safest egress path to the designated muster or lifeboat station.

It was expected that most participants would select the safest route based on the information in the PA announcement. In the SBML study, 67% of participants continued to use the same decision tree, selecting their egress route based on PA information (as shown in Table 3). In the LBT study, only 24% of participants had the same

Table 3 – Resulting decision trees for 15 SBML participants after finishing training module 2 (S5) and module 4 (S9).

<table>
<tr><th>Subject</th><th>Decision rules until test scenario T1</th><th>Decision rules until test scenario T2(F1-F3)</th></tr>
<tr><td>A02, A06
A10, A19
A22, A38
A44, A45
A53, A60</td><td>


</td><td>Remains the same.</td></tr>
<tr><td>A27
A33
A62</td><td>


</td><td>Remains the same.</td></tr>
<tr><td>A29</td><td>


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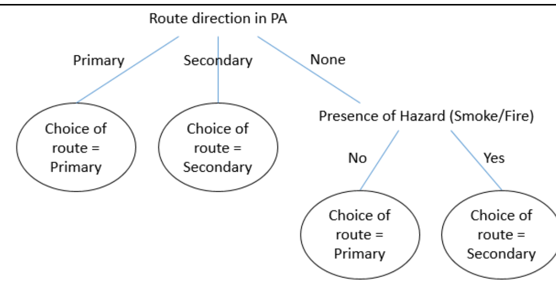

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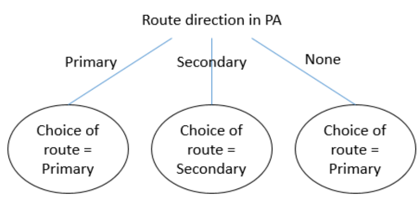
<tr><td>A42</td><td>


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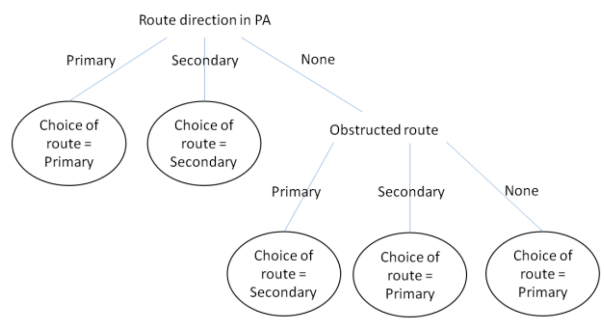

</td></tr>
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decision tree. Similarly, 20% of the SBML participants continued to use the strategy in which the alarm type or end point indicated the route choice in the absence of a PA.

When participants failed to perceive the PA instructions, some individuals put emphasis on different attributes to make their decision. Some participants followed the alarm type and PA, whereas others considered the presence of hazards, or route obstructions. Thirteen percent of participants in the SBML study demonstrated more complex decision trees to manage the emergency conditions. Conversely, the remaining participants in the LBT study (76%) had more varied behaviours. The following summarizes the strategies observed for LBT participants:

- 41% developed complex decision trees that incorporated special conditions for the PA announcements, alarm type or end points, obstructed routes, and hazards.
- 12% selected the same route regardless of the emergency conditions.
- 23% appeared lost. Decision trees were not developed for these participants as they were unable to form a generalization from the knowledge base.

Prediction Accuracy of the Decision Trees

To determine the accuracy of the decision trees, they were used to predict decision making in subsequent scenarios. Specially, they were used to predict the participants' route selection in test scenarios (T1 and T2). The predictions were compared to the actual routes the participants took in those scenarios. The prediction accuracy was calculated based on the average number of successful matches between the decision tree predicted outcomes and the observed outcomes of the participant. Table 4 shows the results for the SBML study. The decision trees were able to predict the route selection of participants with 94% accuracy.

Table 4: Percentage Prediction Accuracy.

Participant No.	% Prediction Accuracy
A02	100
A06	80
A10	100
A19	100
A22	80
A27	100
A29	100
A33	75
A38	100
A42	100
A44	100
A45	100
A53	100
A60	75
A62	100
Average	94

Efficacy of LBT and SBML Training

Overall, the SBML participants' behaviours in responding to emergencies over the course of their exposure to several scenarios gradually converged to a few expected decision trees. Conversely, the LBT participants' behaviours in responding to emergencies diverged. At the alarms recognition phase, the participants in the SBML study had 2 different strategies and the participants in the LBT study had 6 different strategies. In the advanced emergency phase, the SBML participants had 4 different strategies and LBT participants had 10 different strategies for assessing the emergency conditions and safely evacuating the platform. All of the observed route strategies for the SBML participants led to the successful completion of the test emergency scenario.

Many of the LBT participants had a poor understanding of the egress procedures and were overall less compliant with rules. In general, participants in the LBT study put more weight on attributes that were not necessarily useful in making egress decisions. The variability and incorrect behaviours modeled in the decision trees by the LBT training show that this form of training was inadequate for preparing participants for emergency conditions. The SBML training resulted in higher safety compliance and more concise decision trees. This suggests that participants from SBML training were better equipped for managing the emergency scenarios. It is likely that these positive results are because the SBML study placed more emphasis on training participants to pay attention to the PA and act according to the directions of the PA. It may also be due to the fact that the SBML participants were required to practice the task until competence was demonstrated. The results of this study show that SBML training resulted in decision trees that better reflect competence and reduced variance in safety compliance in comparison to the LBT training.

Conclusion

Modelling human behaviour in emergency conditions can be difficult. The paper outlined a cognitive modeling approach that is suitable for modeling decision making and predicting human response in virtual emergency scenarios. The decision tree modeling approach was shown to be appropriate for assessing the training efficacy of two different training programs: lecture based training (LBT) and simulation based mastery learning training (SBML). The visual representation of the participants' strategies in emergency situations was useful in identifying the strengths and weaknesses of the training methods. Decision tree modelling could help inform the design and assessment of future VE training curriculum and predict the performance of general personnel in emergency situations.

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