Distributed Simulation as a Planning Support Tool for Relief Operations

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***Abstract*—During relief operations, the resource management process for planning rescue missions requires a capable and efficient planning cycle to handle time critical constraints. In order to support planning under such circumstances it is necessary to understand all the priorities, constraints, and also the criteria to be utilized during the planning process. Simulations are well established support tools for planning, may be utilized to increase the planner's situation awareness over the area of interest, and also provide the ability to expand the solution space by generating multiple plans for the same situation. The present work is being conducted to establish a distributed simulation environment, with 3D visualization, to address all of the above mentioned issues. Such visualization may help managers, planners and operational people understand the scenario evolution, while also supporting diverse techniques for planning process under the time constraints and uncertainty existing in disaster relief operations.**

***Keywords*—Planning; Distributed Simulation; Relief Operation.**

I. Introduction

During the last few years an increasing number of very large disaster relief operations has been carried out by many different countries and by multiple different organizations to save lives. Common to all disaster scenarios is the need to deal with time as a critical constraint during the planning and coordination of the resources made available to the rescue operation.

In many of those, there is also the transport allocation problem, which is dependent upon the type of disaster (i.e., man-made or natural) and the associated environment transformation. These are also caracterized by a high level of stress, in which people are often unreachable by land or by water and even by air. Thus, a better understanding of the environment and of the ways to reach the affected population increase the ability of the rescuers to deliver expedite and effective relief.

Resource allocation managers need to perform their task with the available resources in a way to prevent sub and super allocation for each place that has to be visited by each kind of available transportation resource [1]. As the terrain conditions may change during the scenario evolution, the planning process must be able to properly represent uncertainty within reasonable time constraints.

Simulation has the potential to help improve planing in such circumstances. Because simulation tools can evaluate different plans at the same time, alternative plans can be generated and plans can be altered in response to changing situations.

A difficult part of the problem is to manage the transportation traffic inside the rescue area. In this case, a tool such a 3D plan visualizer can be used to increase the awareness of possible path interference among the resources (such as air collisions, or path interruption by land slides). Another major issue when planing the transportation traffic is the assignment of resources to execute the missions.

It may only be necessary to identify the optimal route between a small number of points, but in other circumstances rescuing more people in just one mission may become the main goal due to changes to the existing situation. To mitigate these issues, simulation can be used to design and execute different models in parallel, by different teams, making use of the same scenario description.

Such capability is important when using distributed simulations, where a shared environment can be designed and different algorithms can provide different approaches for the same problem under different requirements.

The present research is being conducted to establish a distributed simulation environment that will support mission planning in different situations with 3D visualization. The case study is a flooding situation in the Brazilian state of Santa Catarina and the focus is to generate a planning algorithm to support rescue missions in an environment that evolves during plan execution.

The paper is organized as follows. Section II presents distributed simulation as a planning support tool, while Section III describes the chosen planning approach for the resource allocation problem. A case study illustrates the approach in Section IV and then conclusions and future work are presented in Section V.

II. Distributed Simulation

A simulation is considered as being distributed when it is executed in multiple processors and in different machines that are spread geographically [2]. Benefits of distributed simulations include the ability to divide the processing among several processors, allowing load balance, and to enable different perspectives from the same model during the simulation execution. Also, it is possible to generate multiple models in different processors and integrate them into one simulation by a central controller.

Different architectures were developed to support distributed simulation like the Distributed Interactive Simulation (DIS), High Level Architecture (HLA) and Test and Training Enabling Architecture (TENA). Each architecture has its own purpose and is supported by Commercial Off-The-Shelf (COTS) simulation tools and by the open-source community.

The present work is part of a joint project between academia and industry. The academic partners are the Aeronautics Institute of Technology - ITA (Brazil) and the Center of Excellence in C4I at George Mason University - GMU (USA), while the industry is represented by VT MÄK simulation tools (USA) [3] for the distributed simulation package and LatinMedia (Brazil) [4]. The project uses MÄK's COTS tool package called VR-Forces 4.0 installed in three different machines at ITA's Command and Control Lab and in two machines at GMU's Fusion Lab connected through a VPN between both organizations as depicted in Fig. 1.

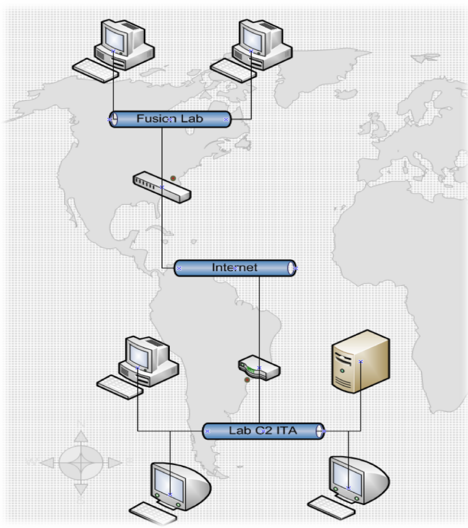

Figure 1. Joint project VPN configuration.

The configuration depicted in Fig. 1 was designed to generate an immersive scenario to support the managing of available transportation resources during relief operations. The challenge is to capture the evolving scenario parameters that can potentially generate changes in the plan during execution and to respond to these by dynamically modifying the plan.

Addressing these challenges will allow for a better understanding of the possible situations, the establishment of metrics and utilities to be utilized by the planning algorithms, which will ultimately lead to the generation of a plan library with alternative plans. The various possible sub-sets of the major plan could then be utilized and substituted during its execution.

The network backbone was implemented using a VPN over the Internet. Setting up this VPN proved to be a challenging task, as it involved the maintainance of minimum connection quality requirements to conduct the experiments via WAN links [5], the setting of multicast routing over Internet, and the provision of an adequate level of security in both labs.

As cited in [5] [6], to provide HLA and DIS services, the network must be able to support error rates bellow 2%, a maximum latency bellow 100 milliseconds, and a strict control over jitter. The requirements are compatible with those for voice/video applications over the Internet [7] as well as for multicast traffic.

To simplify the packet routing one bridge was implemented between the two sites using the OpenVPN Server [8], with all machines running in the same network. To provide security for both sites, the cryptographic's features in OpenVPN were used, adding one new situation: the overhead caused by cryptographic and, consequently, the latency increment. To minimize this impact, we opted for using the LZO library [9]. This library provides a way of compressing real-time applications. As cited by [10], the use of lzo's library enables an overhead reduction of up to 50%, while not significantly increasing local processing.

III. Planning

Planning is an abstract and deliberative process that chooses and organizes actions by anticipating their expected outcomes [11]. The integration of planning with simulation as implemented in this work provides a method that can generate possible actions and then identify gaps and holes on the plan prior to its execution.

In a relief operation, most of the actions are well understood but, in an evolving environment, each outcome is not deterministic and undesired events can reduce the ability of the rescue team to achieve the goal (saving lives). To increase awareness and prevent dangerous situations for the rescue teams it is necessary to identify, depending on the available time, the actions that will promote the desirable outcome based on some criteria, metrics, or utility function from the resource allocation managers' perspective.

A conceptual model for planning is needed. For this work, the conceptual model relies on a state-transition system, which is also known as discrete-event system [11].

Formally, a state-transition system is a tuple $\Sigma = (S, A, P)$, where:

- $S = \{s_1, s_2, ...\}$ is a finite or recursively enumerable set of states;
- $A = \{a_1, a_2, ...\}$ is a finite or recursively enumerable set of actions;
- $Pa(s'|s)$, where $a \in A$, s and $s' \in S$, and P is a probability distribution. For each $s \in S$, if there exists $a \in A$ and $s' \in S$ such that $Pa(s'|s) \neq 0$, we have $\sum_{s' \in S} P(s, a, s') = 1$.

$Pa(s'|s)$ is the probability that if we execute an action a in a state s, then a will lead to a state s'. We call $A(s) = \{a \in A \mid \exists s' \in S.\ Pa(s'|s) \neq 0\}$ the set of *executable actions* in s, i.e., the set of actions that have probability different than 0 to have a state-transition.

To illustrate the above modeling let's consider a system with a person to be rescued and a helicopter that 1) can pick up the victim and bring the person to a safe location; and 2) is able to move from one location to another. The set of states is $\{s_1, s_2, s_3, s_4, s_5\}$ and the set of operators is {move(helicopter,locationFrom, locationTo), embark(victim, helicopter), disembark(victim,helicopter), wait(helicopter, location)}. In our example we have only location $l1$ and location $l2$, helicopter $h1$ and victim $v1$. So, the set of actions is {move($h1, l1, l2$), move($h1, l2, l1$), embark($v1, h1$), disembark($v1, h1$), wait($h1, l1$), wait($h1, l2$)}. Fig. 2 shows the system. The arc (s_1, s_2) is labeled with the action move($h1, l1, l2$), the arc (s_2, s_3) with the action embark($v1, h1$), and so on. Each state transition is *deterministic* in the sense that it leads to another state.

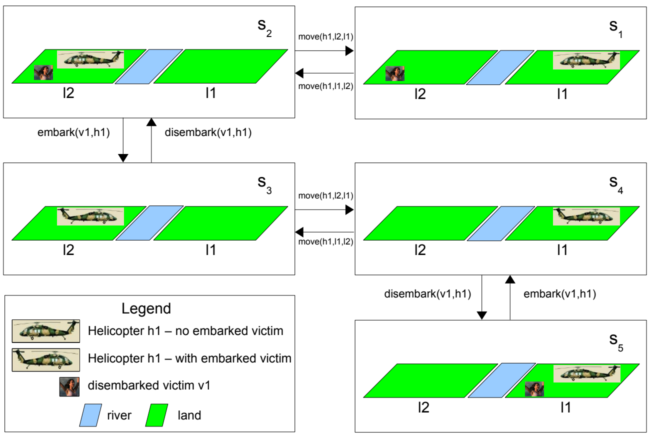

Figure 2. A deterministic state-transition system for a simple domain involving a victim and a helicopter in a rescue mission.

The state s_0 shows the helicopter $h1$ in location $l1$ and a victim $v1$ in the location $l2$. The locations are green areas separated by a river (blue area). The expected goal is to bring the victim $v1$ from location $l2$ to location $l1$ as seen in state s_5. A feasible plan is the sequence {move($h1, l1, l2$), embark($v1, h1$), move($h1, l2, l1$), disembark($v1, h1$),wait($h1, l1$)}.

Fig. 3 depicts a situation with the same set of actions but a different set of states, where the state transition is *nondeterministic* in the sense that it may lead to more than one state. In this case, the likelihood of each possible state is defined by a probability function.

In the state-transition system depicted in Fig. 3 we have a probability of 80% to reach the area with the victim in a non flooded location when the selected action is move($h1, l1, l2$) from state s_1. As a consequence, in 20% of the time the action will produce an undesirable state s_6 in which the victim has either died or moved away from the location during the flooding. The illustration shows the importance of planning under uncertainty and the necessity to be able to change the plan during the execution while identifying a way to still be effective.

Because of the nature of the domain illustrated in Fig. 3, there is a need to deal with uncertainty in a principled way.

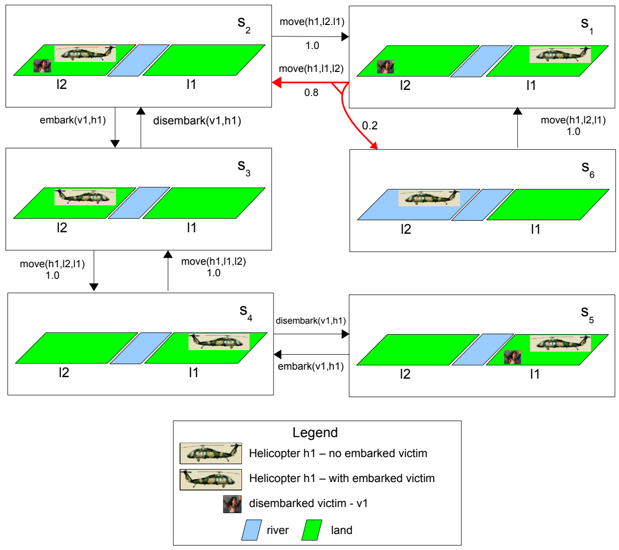

Figure 3. A nondeterministic state-transition system for a simple domain involving a victim and a helicopter in a rescue mission.

The approach commonly taken is to represent the planning problem as an optimization problem [11]. the present work adopts Markov Decision Processes (MDP) [12] conventions listed below:

- A planning domain will be modeled as a *stochastic system*. The uncertainty about actions outcomes is modeled with a joint probability distribution function;
- Goals will be represented by means of *utility functions* that can express preferences on the entire execution path of plan;
- Plans are represented as *policies* that specify the action to execute in each state; and
- The planning problem is seen as an *optimization problem*. The algorithms search for a plan that maximizes the utility function.

Then, a plan will be represented by a *policy* π as a total function mapping states into actions:

$$\pi : S \rightarrow A \tag{1}$$

For the case presented in Fig. 3 a possible policy is:

$\pi_1 = \{(s_1,$ move$(h1, l1, l2)),$ $(s_2,$ embark$(v1, h1)),$ $(s_3,$ move$(h1, l2, l1)),$$(s_4,$ disembark$(v1, h1)),$ $(s_5,$ wait$(h1, l1)),$ $(s_6,$ move$(h1, l2, l1))\}$

Policy executions correspond to infinite sequences of states, called *histories* whose probabilities at a given time are conditionally dependent on those observed in the previous time [11]. A history for the above policy could be $h_0 = \langle s_1, s_6, s_1, s_2, s_3, s_4, s_5, s_5, s_5, ...\rangle$.

Let π be a policy and $h = \langle s_0, s_1, s_2, ...\rangle$ be a history. the probability of h induced by π is the product of all transition probabilities induced by the policy:

$$P(h|\pi) = \prod_{i \geq 0} P_{\pi(s_i)}(s_{i+1}|s_i). \tag{2}$$

Let $C : S \times A \rightarrow \Re$ be a *cost function* and $R : S \rightarrow \Re$ be a *reward function* for a stochastic system Σ. We can define the utility in a state s with an action a as

$$V(s, a) = R(s) - C(s, a) \tag{3}$$

and the utility of a policy in a state as

$$V(s|\pi) = R(s) - C(s, \pi(s)). \tag{4}$$

This generalizes to histories. Let $h = \langle s_0, s_1, s_2 ... \rangle$ be a history and γ a *discount factor*, with $0 < \gamma < 1$. The *utility* of a history h induced by a policy π is defined as

$$V(h|\pi) = \sum_{i \geq 0} \gamma^i (R(s_i) - C(s_i, \pi(s_i))). \tag{5}$$

Let Σ be a stochastic system, H be the set of all the possible histories of Σ, and π be a policy of Σ. Then the expected utility of π is

$$E(\pi) = \sum_{h \in H} P(h|\pi) V(h|\pi). \tag{6}$$

A policy π^* is an *optimal policy* for a stochastic system Σ if $E(\pi^*) \geq E(\pi)$, for any policy π for Σ. So, for a given stochastic system Σ and a utility function, a *solution* to a planning problem is an *optimal policy*.

The MDP framework presented above will serve as the basis for the planning algorithm to be implemented for the case study.

IV. Case Study

The chosen case study is complementaty to the one present in the Command and Control semantic-based framework being developed in ITA, C2MANTICS [13], which demands a web-service capable of automatically generating and suggesting plans for a small Air Force fraction during relief operations. The elected study scenario is based on a flood situation that occurred in 2008 in the state of Santa Catarina, Brazil, on the Itajaí's valley. The city of Itajaí was completely flooded and the higher areas suffered land slides due to the continuos flow of heavy rain in the region. A hundred and twenty-five people died on that event and many different resources were allocated to support the relief operation.

As a way of simplifying this initial part of the work, we restricted the resource allocation to consider only helicopters as transportation assets and people as the subjects to be transported. The cost and reward, as well as the state-transition system can be seen in Fig. 4.

A. Problem Description

Given a state-transition system $\Sigma = (S, A, P)$:

- The set of states $S = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}\}$;
- The set of actions A is represented in a similar fashion of the example in Section III; and
- Let $P_{move}(s'|s)$ be the probability of the action *move* the helicopter from one state s to another state s' as described in Fig. 4.

The state s_1 represents the apron from Navegantes' airport and the state s_{10} represents the place where the victims should stay after each rescue mission.

The cost represents the helicopter movement from one location to another (cost = function of the distance between places) and the reward is equal to 1 when it is possible to rescue people in states s_2 through s_9 and when people are disembarked in state s_{10}. The utility function is used to minimize the cost.

The policy π_1, to be evaluated, will dictate the schedule for each day of operation. The joint probability distribution of the state-transition system can change on dayli basis, according to the weather conditions and flooding situation.

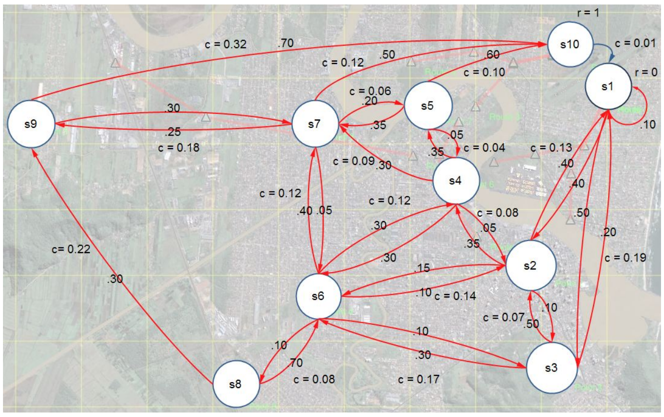

Figure 4. Costs and rewards for policy π_1 in the case study state-transition system. Red edges are nondeterministic.

B. Solving the problem

The policy π_1 was evaluated using the Value Iteration algorithm [12] [14] with different discount values, as seen in Fig. 5. The higher utility value was reached based on the *discount factor* $\gamma = 0.9$ after 15 iterations. Taking only

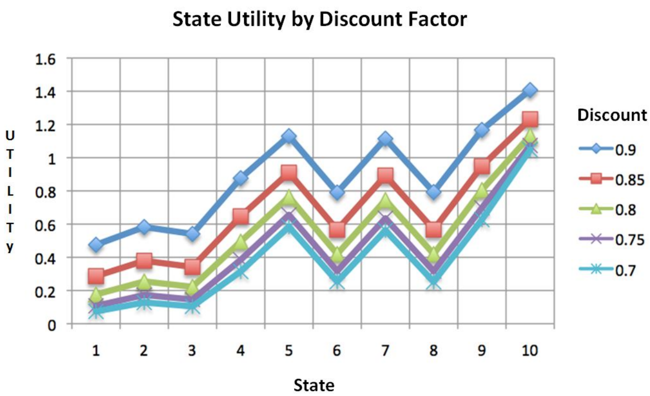

Figure 5. State Utility for policy π_1 based on Value Iteration algorithm and by the different discount factors.

rewards in consideration makes the utility to be higher for the states that are near the state s_{10} in terms of connections between states. So, changing the reward function will generate different perspectives from the problem as the flooding situation evolves.

C. Preliminary Simulations

The 3D terrain was developed by the Centro de Computação de Aeronáutica de São José dos Campos (CCA-SJ) in two different models, before and after the flooding situation. Fig. 6 shows the flooded model where a rescue mission is taking place inside the city of Itajaí. By the time of this writing, the planner is not yet integrated into the VR-Forces tool and the mission has to be manually programmed in order to see the possible problems during a mission execution with more than one helicopter at the same time.

Preliminary results have shown that time is a constraint that has to be observed and also treated during the policy definition because the helicopters have landing procedures and have to wait people embark. If the helicopter makes more than two movements, the resulting time lapse will influence its availability to perform another mission that could have a higher priority. This illustrates that there is a schedule problem that has to be solved during mission execution.

As the situation evolves, it is interesting to change the policy to allow for increased flexibility in the helicopters schedule, as well as to support different allocations based on the terrain conditions. Such an approach will be tested in future implementations of this scenario, which will also relax the current modeling restrictions by incorporating trucks and boats as new transportation assets available to the managers.

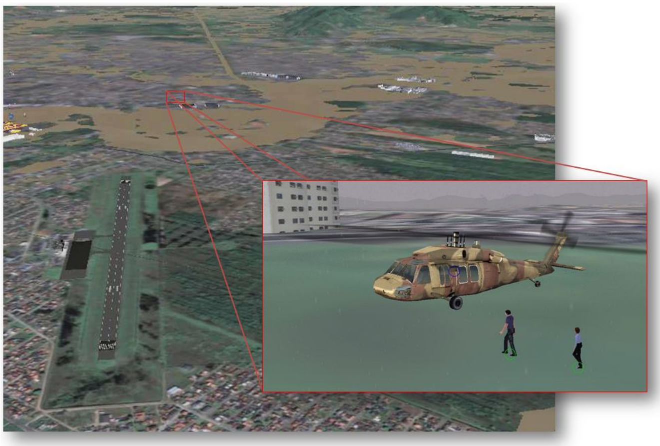

Figure 6. Santa Catarina's flooding scenario in VR-Forces 4.0 [3].

As previously noted, the network requirements to run one simulation experiment have many similarities to those observed in a voice/video real-time application. During our experiments, an evaluation technique based on the e-model [15] was used to assess the quality of the 3D simulation.

V. Conclusion and Future Work

The present work is being developed as a testbed for planning, including simulation and visualization of ongoing relief operations. The aim is to have planning algorithms that will support resource management during the scenario evolution. To address the uncertainty and time constraints always present in such circumstances, we are investigating tools and methods to better understand the factors that can improve the effectiveness in rescue missions.

The effort is being conducted between Aeronautics Institute of Technology (ITA - Brazil) and the C4I Center at George Mason University (GMU - USA) with support from VT MÄK and LatinMedia. The current status of the research indicates that it is necessary to have a different policy for each situation that can be generated and evaluated through Markov Decision Process algorithms (MDP). The case study used in our work is a flooding scenario in the state of Santa Catarina.

Regarding the future work, the next step is to integrate the planning algorithms inside the simulation tool and also implement a scheduler algorithm to automatically allocate resources after choosing the optimal policy. The case study is also being developed to achieve a higher resolution. Finally, we are also entertaining the possibility of modeling the planner as a web service, which will allow its utilization in a real decision support system for air operations planning during disaster relief operations.

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