Improving Air Traffic Management through Agent Suggestions

(Extended Abstract)

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ABSTRACT

Providing intelligent automation to manage the continuously increasing flow of air traffic is critical to the safety and economic viability of air transportation systems. However, current automated solutions leave existing human controllers "out of the loop" rendering the potential solutions both technically dangerous (e.g., inability to react to suddenly developing conditions) and politically charged (e.g., role of air traffic controllers in a fully automated system). Instead, this paper proposes a distributed agent based solution where agents provide suggestions to human controllers. Results on traffic flow around New York show that the suggestion agents can improve system performance by up to 25% over that of human controllers alone, and that these results degrade gracefully when the number of human controllers that follow the agents' suggestions declines.

Categories and Subject Descriptors

I.2.11 [**Computing Methodologies**]: Artificial Intelligence

General Terms

Algorithms, Performance

Keywords

Air Traffic Control, Multiagent Systems, Optimization

1. INTRODUCTION

Air traffic is expected to increase threefold over the next two decades, adding added pressure to an already congested system, where economic loss due to delays is measured in the tens of billions of dollars [1]. Unlike many other flow problems where the increasing traffic is to some extent absorbed by improved hardware (e.g., more servers with larger memories and faster CPUs for internet routing) the air traffic domain needs to find mainly algorithmic solutions, as the infrastructure (e.g., number of the airports) will not change significantly to impact the flow problem.

Multiagent approaches provide an appealing solution to this problem and have been successfully applied to many air traffic routing problems [2, 3, 4]. In this paper we propose an alternative multiagent approach where the agents provide suggestions to human controllers. This approach aims to merge the benefits of automation with the remarkable safety record of current air transportation systems. In this formulation, the agent actions go through a "filter" (the air traffic controllers) before resulting in a particular reward.

The overall system evaluation criterion in this work is based on the linear combination of the amount of congestion in a particular region of airspace and the amount of measured air traffic delay, and is given by $G(z)$ as a function of the system state z:

$$G(z) = -((1-\alpha)B(z) + \alpha C(z)) , \qquad (1)$$

where $B(z)$ is the total delay penalty for all aircraft in the system, and $C(z)$ is the total congestion penalty. The relative importance of these two penalties is determined by the value of α. To obtain the values for both $B(z)$ and $C(z)$, we use FACET (Future ATM Concepts Evaluation Tool), a physics based model of the US airspace that was developed to accurately model the complex air traffic flow problem (described in [4]).

2. SUGGESTION AGENTS

Though the system performance is measured by G, we assume that each human controller is mostly concerned with minimizing congestion. This is a reasonable assumption, since congestion is a primary concern as it affects safety as well as the controllers workload. In addition, we also assume that they have some incentive to follow the suggestion from the agent. We therefore model a controller's reward as a linear combination of controller's intrinsic goal of wanting to reduce congestion, and the controller's imposed incentive to follow the agent's suggestion:

$$H_i(z) = -(1-w)C(z) + wK_i(z_i, x_i) , \qquad (2)$$

where z is the control of the human controller, x is the suggestion by the agent, w is a weight and $K(z, x)$ is the incentive for the human to follow the suggestion. In this paper the incentive will simply be the numerical difference between the agent's suggestion and the human's suggestion: $K_i(z_i, x_i) = |z_i - x_i|$. This incentive intuitively reinforces the notion that controllers are more likely to follow suggestions with which they agree. Note that when $w = 0.0$ the agents' suggestions are completely ignored and when $w = 1.0$ the human controller's reward is solely based on complying with the agents' suggestions.

Agents in the system are locations throughout the airspace called "fixes." Each agent is then responsible for setting val-

Cite as: Title (Short Paper), Author(s), *Proc. of 8th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2009)*, Decker, Sichman, Sierra and Castelfranchi (eds.), May, 10–15, 2009, Budapest, Hungary, pp. XXX-XXX.

ues of "miles in trail" (MIT) which is the distance aircraft have to keep from each other while approaching a fix. Using agents that set MIT values directly has proven to be an effective method of controlling the flow of aircraft [4].

The learning algorithm used by the agents is simple table-based immediate reward reinforcement learner. After taking action a and receiving reward R an agent updates its value for action a, $V(a)$ (which is its estimate of the value for taking that action) as follows: $V(a) \leftarrow (1-\lambda)V(a) + (\lambda)R$, where λ is the learning rate. At every time step, the agent chooses the action with the highest table value with probability $1-\epsilon$ and chooses a random action with probability ϵ. In the experiments described in this paper, λ is equal to 0.5 and ϵ is equal to 0.25.

While maximizing the system reward directly has been successfully used in small multiagent learning problems, it does not scale well since the impact of a single agent's actions of the system reward is relatively small. To alleviate this problem, we use a more agent-specific reward [4]:

$$D_i \equiv G(z) - G(z - z_i) \; , \tag{3}$$

where z_i is the action of agent i. In this reward, all the components of z that are affected by agent i are removed. Intuitively, this reward quantifies the impact of an agent on the system.

3. EXPERIMENTAL RESULTS

To show the performance of the suggestion agents, we perform experiments using air traffic data from the New York City area. In each experiment there are 10 agents, with each agent being assigned a fix located on one of the inbound flows into New York. There are approximately 681 aircraft going through the 10 fixes over a 14 hour time window.

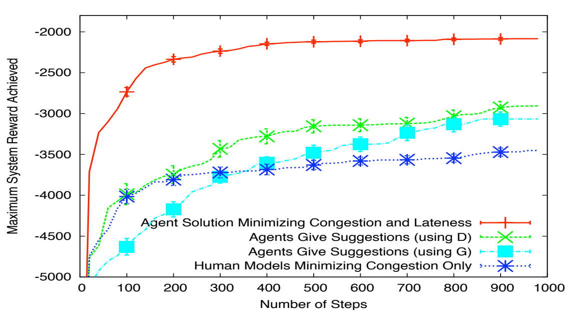

Figure 1: Impact of suggestion agents on system performance.

Figure 1 shows the performance of the suggestion agent system when $w = 0.6$. It is clear that when human controllers are only minimizing congestion, they do not perform well at maximizing the system reward that includes both congestion and lateness. (This is indeed precisely the situation right now, where air traffic controllers focus on local and congestion based performance criteria, whereas the full system performance has many components including lateness and congestion.) The fully automated system performs the best, and the results show that agent suggestions are beneficial to the system.

Figure 2 shows that the more humans follow the agents, the better the system performance becomes for agents using the difference reward. Note however that even at $w = 1$ when the only goal of human controllers is to follow their

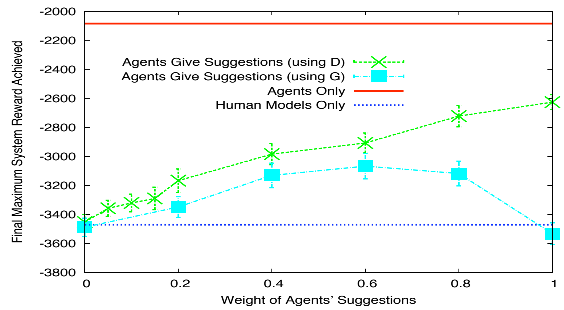

Figure 2: Impact of "participation" by humans.

suggestion agents, the system still does not perform as well as in an agent-only system. This lower performance can be explained by this system having two coupled learning cycles, where the suggestion agent has to learn how to give good suggestions, and the human controller has to learn to follow these suggestions. Since the feedback to the agent is more indirect, learning is slower.

The learning interaction between human controllers and agents directly maximizing the system reward, G, is even more interesting. Paradoxically, beyond a certain point increasing the weight of the agents' suggestions reduces performance. This can be explained by an instability when both agents and controllers are learning in the same system. When agents are slow to learn the impact of their suggestions, the human controller may just perceive those suggestions as noise and not be able to learn to follow them. This leads to a situation where no effective signal is being sent back to the agent.

This extended abstract shows that suggestion agents can improve the system performance by up to 25% on a real world air traffic problem, and that system performance degrades gracefully when the air traffic controllers start to ignore the suggestion agents. Extensions of this work include improved models of human controllers, more comprehensive system evaluation functions, and a larger airspace including multiple hubs. We are currently investigating such extensions with the ultimate goal of providing a safe, reliable and implementable air traffic control algorithm that while keeping humans in the loop will both improve the efficiency of the humans and allow the capacity of the airspace to increase to accommodate the expected rise in air traffic.

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