2005

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PILOTS, AIRSPACE COMPLEXITY, AND STRATEGIC CONFLICT AVOIDANCE

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Some future air traffic management concepts seek to place more separation responsibility on the pilot in order to achieve greater aircraft operating autonomy. Separating one’s own aircraft from others in something other than a see-and-avoid environment, however, would pose fundamentally new demands and challenges for pilots, and it is likely that new automation and display tools would be needed. Ideally, an automated strategic conflict avoidance system would behave consistently with pilot expectations and take pilot interests into account when suggesting resolution strategies. It might also recognize situations that pilots may have difficulty detecting and resolving on their own. At this time, little is known about how pilots perceive airspace complexity in self-separation tasks. In this study, we used a Cockpit Display of Traffic Information (CDTI) with an embedded strategic conflict avoidance aid to help fourteen commercial transport pilots detect and resolve a series of strategic conflict situations. We then assessed their performance with and without the aid, recorded and analyzed pilot ratings of aid effectiveness and usability, and used a neural network model to associate complexity ratings with airspace characteristics to determine which sets of characteristics most heavily influenced pilot perceptions of airspace complexity. The results of this analysis provide insight into what aspects of airspace configuration may have the greatest influence on pilot perceived workload and difficulty understanding conflict situations.

Introduction

Several emerging concepts for future air traffic management systems seek to transfer some, or all, of the responsibility for aircraft separation from air traffic controllers to pilots. In most concepts, such as the “Free Flight” concept (RTCA, 1995), this is done to grant airlines and pilots more autonomy, under the assumption that this will lead to more efficient routing and allow operators to optimize their routes or the flow of traffic within their fleets.

For airline and instrument pilots, this will represent a new set of responsibilities and is likely to add to their workload. Furthermore, flight management responsibilities may sometimes make it difficult or impossible to also attend to self-separation responsibilities. This suggests that some form of automated assistance will likely be needed.

In this study, we investigated the usefulness and usability of a Cockpit Display of Traffic Information (CDTI) with an embedded automatic strategic conflict detection capability, coupled with a route planning aide that assessed the presence of conflicts associated with modified routes, in a variety of strategic conflict situations. Recognizing the potential for mismatches of interests, solutions, and expectations between the pilot and automation, we also used a neural network model to better understand what aspects of the airspace, based on the positions and trajectories of nearby traffic, most contributed to pilot perceptions of airspace complexity.

In particular, the questions we were interested in included:

• What characteristics of the airspace (positions and velocities of other aircraft) affect pilot perceptions of airspace complexity?
• How much benefit would a decision aid be in detecting and resolving conflicts?
• How readily would pilots accept and use such an aid?
• What characteristics of the airspace affect the ability of pilots to reliably detect and resolve conflict situations without help?
• How much complexity can pilots reliably handle before decision making and route replanning performance start to deteriorate?

The results of this study should help guide the development of automated route planning and conflict resolution aids and ensure that such aids adequately account for pilot interests and expectations. It should also help guide the development of airspace management procedures involving aircraft with self-separation capabilities.
Method

This study brought two bodies of prior work together to support the effort: a CDTI developed at NASA, and prior work using neural networks to understand how air traffic controllers are influenced by airspace complexity factors.

CDTI

We used a CDTI/route planning aid (hereafter referred to simply as the “aid”) that was already under development at NASA (Johnson, Battiste, Delzell, Holland, Belcher, & Jordan, 1997). The display, shown in Figure 1, depicts own aircraft position at the lower center of the display and nearby traffic represented as chevron symbols. These symbols are green when the other aircraft are below own-ship, white when at the same altitude, and blue when above. When the system detects a conflict, ownship and the conflicting aircraft turn amber, an amber connecting line is drawn to show the projected conflict position, and an audible alert is given. In addition, aircraft that may come close to own-ship but do not currently conflict are shown in amber outline without an alert to help the crew monitor traffic that might merit special attention.

Figure 1. CDTI showing a projected conflict

Airspace Complexity Factors

A number of prior studies (Chatterji & Sridhar, 2001; Kopardekar & Magyarits, 2002; Kopardekar, 1997; Mogford, Guttman, Morrow, & Kopardekar, 1995) have examined the effect of airspace complexity factors on air traffic controller perceptions of airspace complexity. Various sets of factors have been introduced by a variety of authors, but they usually include parameters associated with the number of aircraft in an area, the number of aircraft within an altitude band, the number of aircraft changing trajectory either laterally or vertically, the presence or absence of conflict conditions, the angle of convergence in a conflict, and others. The number of these measures suggested by various authors jumped after the RTCA free-flight concept (RTCA, 1995) because this concept included a notion of “dynamic density” characterized by airspace complexity factors; a given airspace would be under either free-maneuvering rules or positive control depending on its dynamic density.

We surveyed the collection of airspace complexity factor lists that had been compiled, eliminated those factors that could only relate to ground-based control (and therefore were not relevant to self-separation), and then eliminated factors that were essentially identical to arrive at a list of potentially relevant and unique factors. We then collected these factors into 21 sets for use with the neural network.

Experiment

Fourteen commercial pilots, all male and all with glass cockpit experience, participated in the experiment, which was performed on a laptop computer. The pilots were asked to resolve fourteen conflict situations, which had been designed to cover a range of difficulty levels from very low to very
high, and to include a variety of conflict types (two vs. multiple aircraft involved, head-on conflicts vs. shallow-angle conflicts, and conflicts with aircraft that were changing altitude to or through own altitude). Prior to performing in the experiment trials, the pilots were given a short training presentation about the nature and procedure of the study, filled out demographic questionnaires, and completed six training trials.

Each trial began with the traffic configuration appearing, detected conflicts shown, and the display freezing so the pilot could study the situation. A rating box was displayed so the pilot could rate the complexity of the situation on a three point scale. The pilot could examine the flight and flight plan information for any aircraft on the display, and did not need to enter the complexity rating until fully understanding the situation. We measured the time from scenario start until the pilot entered the complexity rating in hopes that this time measure could serve as an objective measure of complexity (under the theory that it would take more time to understand a more complex situation). As it turned out, there was no significant correlation between the time required to enter the complexity ratings and the ratings themselves.

After the pilot entered the complexity rating for a given scenario, the display would resume motion and the pilot would have the opportunity to adjust the route to resolve conflicts. In half of the experiment trials (counterbalanced for scenario and order), the pilot would be provided with real-time feedback from the aid about whether the adjusted route had resolved the initial conflicts and whether it had created any new ones. In the other half, this feedback was not given; the initial conflict continued to be depicted and the pilots were asked to judge on their own whether the adjusted route was conflict-free.

When the pilot was satisfied that the adjusted route was free of conflicts, he would enter the route into the system, which would then provide feedback that the new route had been activated. Then, another rating box was displayed, this one asking the pilot to rate the difficulty of resolving the situation on a five point scale. Once this rating was provided, the experiment would move on to the next trial (or end).

After completing the experiment trials, the pilots filled out a survey covering their attitudes regarding the usefulness and usability of the aid. The pilots were paid $100 for their participation.

**Analysis**

The list of measures included:
- the complexity ratings
- the time required to enter these ratings
- airspace configuration at the time of these ratings
- the difficulty ratings
- total completion time for each trial
- whether any conflicts remained at the end of each trial
- pilot ratings of aid usefulness and usability.

We tested the effects of the aid on complexity and difficulty ratings using repeated-measures regression analyses as well as tests of differences in regression coefficients. Repeated-measures Analysis of Variance (ANOVA) methods were used to determine the effects of the aid on the accuracy and total time of resolving conflicts. Finally, we evaluated the pilot ratings (on a seven point scale) of aid acceptability by inspection.

The neural network analysis was more involved. As mentioned earlier, the airspace characteristics, as represented in terms of the selected complexity measures, were recorded at the time of the entered complexity ratings. This allowed us to associate the complexity measures with the subjective complexity ratings. We then trained a neural network to reproduce the aggregate complexity ratings through an iterative feedback process, as shown in Figure 2.

**Figure 2:** The neural network used iterative back propagation to “learn” how to produce complexity ratings representative of the pilot ratings.

Through this iterative back propagation process, in which the network attempted to reproduce the aggregate pilot complexity ratings with each of the 21 sets of complexity factors, we were able to determine which sets of factors produced the best match between pilot ratings and the neural network outputs. In other words, we determined which set of factors caused the network’s behavior to most closely match that of the pilots.
Results

In summary, the results demonstrated that the aid improved pilot avoidance of conflicts and was generally accepted and liked by the pilots. We were also able to identify a set of eleven airspace complexity components out of the original 21 that appear to most heavily influence pilot complexity ratings.

One of the most informative pilot performance results had to do with the comparison of the complexity and difficulty ratings for each scenario. This is because of the possibility that the aid might be able to make complex situations relatively easy to resolve. To facilitate this comparison, we used a three point scale for complexity ratings and a five point scale for difficulty ratings to discourage subjects from merely repeating their complexity ratings, given at the start of the scenario, in the difficulty ratings given at the end.

The reason for suspecting that the aid might make complex situations easy to resolve had to do with how the aid transformed the nature of the task. Without the aid, the pilot had to mentally visualize how the airspace situation would change over time. With the aid, the pilot had to merely adjust the route until none of the aircraft symbols and vectors were yellow. This transformed the task from a complex, multidimensional visualization involving multiple targets to a simple binary judgment.

Indeed, we found that the correlation between these two ratings dropped significantly when using the aid, from $r = 0.76$ with the aid off (in the trials where no assistance was provided during route adjustment) to 0.62 with the aid on (two-tailed alpha = .05). This demonstrated that the aid effectively decoupled the difficulty of resolving the scenario from the conceptual complexity of the scenario.

We also found that subjects who resolved conflicts first using the aid rated the overall complexity of all scenarios as more complex than those who resolved conflicts first without the aid (F(1, 12) = 5.00, p < .05). This suggested that using the aid informed the subjects about the true complexity of scenarios, perhaps by showing them conflicts that they would not have otherwise noticed. This may have caused them to better appreciate the complexity of scenarios they later attempted to solve without the aid.

As expected, subjects resolved conflicts more accurately when using the aid (88% resolved) than they did without the aid (77% resolved). (With one statistical outlier removed, these figures were 90% and 76% respectively.) However, it took pilots longer to resolve conflicts when using the aid. This may reflect the absence of feedback when attempting to resolve conflicts without the aid; without information that the adjusted route was conflict-free, subjects may have entered the new route more quickly than they would have with feedback that there were still conflicts present.

We used a seven point scale to measure pilot opinions about the aid’s usefulness and usability. In general, pilots gave the aid favorable ratings for both. They indicated that they would like to use the aid in a free-flight environment, but they expressed concern about the proposed changing roles of air traffic controllers and pilots; several of the subjects commented that they would prefer to retain positive ground control, but that if they had to operate in a free-flight environment, they would value the assistance of the proposed aid. They also indicated that they were not confident resolving conflicts without the aid (nine subjects expressed lower than neutral confidence, three higher than neutral, and two neutral).

In order to learn how to approximate the pilots’ complexity ratings, the neural network had to be given an aggregate set of ratings (low, medium, high) that represented the “consensus” rating of the group. To do this, we calculated, for each scenario, a weighted average rating with a floor function to match the weighted average to the rating scale. Taking this weighted average as the aggregate rating for each scenario, we were able to assess the representativeness of the aggregate ratings by calculating the proportion of pilots whose ratings agreed with the aggregate, for the three levels of rating. This is shown in Table 1.

<table>
<thead>
<tr>
<th>Aggregate</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>69.6%</td>
<td>28.6%</td>
<td>1.8%</td>
</tr>
<tr>
<td>Medium</td>
<td>30.5%</td>
<td>62.8%</td>
<td>6.7%</td>
</tr>
<tr>
<td>High</td>
<td>7.2%</td>
<td>35.7%</td>
<td>57.1%</td>
</tr>
</tbody>
</table>

*Table 1. The proportion of pilots whose ratings agreed with the aggregate ratings*

We then used this aggregate rating set as the criterion to be approximated by the neural network through the back propagation process. In general, the network solution stabilized after about a thousand iterations. The proportion of neural network ratings that matched the pilot ratings is shown in Table 2.
Table 2. The proportion of neural network ratings that agreed with the aggregate pilot ratings

<table>
<thead>
<tr>
<th>Pilot</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>68.3%</td>
<td>30.8%</td>
<td>0.9%</td>
</tr>
<tr>
<td>Medium</td>
<td>14.4%</td>
<td>81.7%</td>
<td>3.9%</td>
</tr>
<tr>
<td>High</td>
<td>0%</td>
<td>43.5%</td>
<td>56.5%</td>
</tr>
</tbody>
</table>

Table 2 shows that the neural network did a very good job of emulating the pilot ratings. With the neural network trained to behave approximately as the pilots did, we examined how well it performed with the various sets of airspace complexity components, reasoning that the set of components that gave the best match between the neural network and pilot ratings would best represent the set of influences on the pilot’s own perceptions.

Several sets of components scored relatively well, differing in how well they matched either the high or low ends of the scale (that is, some sets closely matched the low complexity ratings but did less well on the high, while others did the reverse). One set that showed the best balance across the scale and contained a relatively sparse number of components included the following components:

- the total number of aircraft in the scenario
- the number of climbing, cruising, and descending aircraft
- measures of horizontal and vertical proximity
- amount of time remaining before conflict
- the ratio of the standard deviation of speed to the average speed of aircraft in the scenario
- the number of unique alerts ongoing
- the presence or absence of an alerting state
- the presence of shallow angle conflicts (which are particularly difficult for pilots to recognize and project).

For this set of components, the neural network matched the pilots’ aggregate “low” rating 68.3% of the time, the “medium” rating 81% of the time, and the “high” rating 52.2% of the time.

Conclusions

These results provide an initial step toward understanding how pilots conceptualize the local airspace in strategic conflict situations, and may help us better understand what capabilities and behaviors they will expect and need in a strategic conflict avoidance aid for a free-maneuvering environment. Ideally, these and the results of following studies will help designers compensate for known pilot performance weaknesses in such situations (such as poor ability to recognize shallow angle conflicts and to visualize conflicts involving aircraft with changing altitudes). They should also ensure that future self-separation aids take pilot interests and expectations into account, thus avoiding potentially surprising behaviors in potentially dangerous situations.

In the next steps for this work, we hope to add real-world maneuvering constraints such as weather and restricted airspace, and introduce traffic with changing flight plans, dynamic maneuvering, and possibly unreliable intent information. We would also like to compare pilot solutions to such conflicts with optimum solutions to better understand pilot strengths and weaknesses in such circumstances, determine at what levels of complexity pilot performance breaks down (and automation is required), and how pilots can effectively manage failures of the conflict aid in complex traffic environments. We hope that these results will inform not only future technology development in this area, but also the development of airspace management and flight deck procedures in free-maneuvering environments.

References


Kopardekar, P. (1997). Dynamic density metric variables. (Federal Aviation Administration, William J. Hughes Technical Center, National Simulation Capability Program.)

