Empirical Test of Conflict Probability Estimation

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Abstract: The conflict probability estimation (CPE) procedure presented in earlier papers is tested with real air traffic data. The CPE procedure estimates the probability of conflict for pairs of aircraft with uncertain predicted trajectories. In earlier papers, the CPE algorithm itself was successfully tested by Monte Carlo simulation, but in this paper the simplifying assumptions and the stochastic error model on which it is based are also tested by applying the algorithm to real air traffic data. Only level flight is considered in this paper. The basic trajectory prediction error statistics of the Center/Tracon Automation System (CTAS) are computed and presented, then the CPE results are computed and categorized according to prediction time and path crossing angle. The expected and the actual number of conflicts matched well for most categories of predicted encounters and matched acceptably well for all categories. The feasibility of CPE has therefore been demonstrated.

Introduction

The economics and efficiency of air transportation in the continental U.S. could be improved significantly if the current routing restrictions were relaxed to allow more direct or optimal trajectories. The current system of static jet routes imposes structure on the en-route airspace, which helps to maintain the safe and orderly flow of traffic, but also forces aircraft to fly indirect, zig-zag routes. Fortunately, new decision support systems are being developed for air traffic management (ATM) that will allow safety to be maintained without a static en-route airspace structure. The ultimate goal is "Free Flight," which could save the airline industry several billion dollars per year.

The safety and efficiency of Free Flight will benefit from automated conflict prediction and resolution advisories. Conflict prediction is based on inexact trajectory prediction, however, and is itself therefore inexact. The farther in advance a prediction is made, the less certain it is, particularly in the along-track direction. For better efficiency, aircraft are usually flown at constant airspeed or Mach number rather than constant ground-speed, and the uncompensated effects of wind modeling and prediction errors accumulate with time. A method is needed, therefore, to estimate the probability of conflict, where a conflict is defined as two or more aircraft coming within the minimum allowed separation distance of each other. The minimum allowed horizontal separation for en-route airspace is currently 5 nmi. The vertical separation requirement above 29,000 ft altitude (FL290) is currently 2000 ft; below FL290 it is 1000 ft. Each aircraft is therefore at the center of a conflict zone that is a vertical cylinder 10 nmi in diameter and either 2000 or 4000 ft high.

The conflict probability estimation (CPE) procedure, which was presented in earlier papers [1, 2], estimates the probability of conflict for pairs of aircraft with uncertain predicted trajectories. The trajectory prediction errors are modeled as normally distributed (Gaussian), and the two error covariances for an aircraft pair are combined into a single, equivalent covariance of the position difference or relative position. A coordinate transformation is then used to derive an analytical solution. That solution is exact for level flight, given certain reasonable assumptions, and is approximate for non-level flight. The CPE algorithm has been programmed in C++ and integrated into the Center/Tracon Automation System (CTAS) [3], a decision support system developed at NASA Ames for air traffic controllers. CTAS has been tested at several of the Air Route Traffic Control Centers (ARTCC) operated by the Federal Aviation Administration (FAA). The CPE software is modular and can also be used in ATM decision support tools other than CTAS.

In previous papers, the CPE algorithm was tested by Monte Carlo simulation. That simulation successfully tested the algorithm itself but not the assumptions and the stochastic error model on which the algorithm is based. In this paper, the algorithm, the assumptions, and the error model are all effectively tested by applying the algorithm to real air traffic data. Only level flight above FL290 is considered in this paper. No accounting is done for aircraft type or the availability of a flight management system (FMS), nor are the parameters of the error model calibrated based on results of this study. Also, no wind-error cross-correlation model was used, which particularly affects encounters with small path crossing angles. Lots of room for improvement remains, therefore. The results to be presented are merely intended to demonstrate the basic feasibility of CPE rather than show its ultimate performance potential.

The paper is organized as follows. First, a method

[0]This paper was presented at the 2nd USA/Europe Air Traffic Management R&D Seminar (ATM-98) in Orlando, Florida in December 1998. Russ Paielli can be reached at NASA Ames Research Center, 210-10, Moffett Field, CA 94035-1000 or by email at rpaielli@mail.arc.nasa.gov

called altitude shifting is outlined, which allows a representative air traffic data sample to be collected without requiring any separation standards to be violated. Next, the CTAS flight data recording is discussed. Then the data analysis and processing procedure is described, which involves the processing of the prediction data from CTAS by three separate programs in sequence. The statistical results are then laid out: first the raw CTAS prediction error statistics are computed and presented, both in terms of trajectory prediction error and conflict prediction error; then the CPE accuracy is evaluated and presented. Finally, a conclusion is presented.

Altitude Shifting

A fundamental problem with using real air traffic data to test the CPE algorithm is caused by the fact that conflicts must be resolved by the responsible human air traffic controller. Such human intervention corrupts the statistical sample, even if the aircraft pairs for which it occurs are discarded (as any good pollster knows, selective discarding of samples can bias results). Because controllers obviously cannot stop resolving conflicts, some strategy is required to approximate a valid statistical sample. The method used in this paper, which will be referred to as altitude shifting, is to pretend that pairs of aircraft flying level are at the same altitude when in fact their altitudes are separated by at least the legally required vertical separation. In order to focus on large commercial transport aircraft, furthermore, only aircraft at high altitudes are considered.

Only aircraft pairs in level flight over FL290 with a predicted altitude separation from 2000 to 5000 ft are used, therefore, and the altitude separation is ignored. Those pairs cannot be in actual conflict as long as they maintain constant altitude, so controllers have no reason to intervene (unless, of course, a third aircraft is involved, but that is statistically independent of the conflict status of the original pair). A reasonable approximation of a valid statistical sample is thereby obtained. This entire paper is therefore based on a two-dimensional model: violation of the *horizontal* separation requirement alone is counted as a conflict.

The implicit assumption of altitude shifting is that horizontal winds do not vary with altitude, which is is obviously not exactly true. The effect of the error in this assumption is difficult if not impossible to determine, but altitude shifts are limited to 5000 ft in this paper to limit the effect. For convenience, the following terminology is defined. The phrase "an altitude shift of xxxx ft" (or, alternatively, "an xxxx-ft altitude shift") means that aircraft pairs with altitude separations less than xxxx ft or more than 5000 ft have been discarded, and the remaining pairs have been conceptually "shifted" to a common altitude. Both a 2000-ft and a 4000-ft altitude shift will be considered in this paper. The advantages and disadvantages of each are discussed next.

Above FL290, flight levels separated by 2000 ft are used for nominally "opposing" traffic. For example, FL290, FL330, FL370, and FL410 are used for traffic with a positive easterly component of velocity, whereas FL310, FL350, and FL390 are used for traffic with a positive westerly component. To simulate a sampling at the same altitude, therefore, an altitude shift of 4000 ft must be used. If an altitude shift of 2000 ft is used, approximately ten times more samples are obtained because the traffic tends to be going in opposite directions, but large-angle encounters are overrepresented. The statistical samples are still perfectly good for testing the CPE algorithm, but they are not representative of the types of encounters that controllers see in practice. Rather than simply discarding the large number of samples obtained with a 2000-ft altitude shift, results are presented in this paper separately for both the 2000-ft and the 4000-ft altitude shifts.

Although the CPE algorithm applies to non-level flight, it would much more difficult to test for non-level flight because controllers are forced to be more conservative and to intervene in many cases for which the altitude separation might already be sufficient. This unpredictable intervention might corrupt the statistical sample and would be difficult to eliminate without a large altitude shift. Also, the simple two-dimensional model used in this paper would not be appropriate. For those and other reasons, the scope of this paper is limited to level flight.

Data Recording

The CTAS Trajectory Synthesizer predicts aircraft trajectories, then the Conflict Probe determines whether any aircraft will come into conflict if no controller intervenes. Trajectory prediction involves complex dynamic modeling based on current estimated position and velocity, flight plan, and predicted winds aloft. It is inexact, primarily because of wind modeling and prediction error and secondarily because of tracking, navigation and control error. The positions and velocities are currently based on radar tracking, and are provided, along with the flight plans, by the FAA at their ARTCC facilities. The wind predictions are provided by the Rapid Update Cycle (RUC), a weather prediction system operated by the National Center for Environmental Prediction (NCEP) for the National Oceanic and Atmospheric Administration (NOAA).

The CPE algorithm requires predictions of position and velocity for pairs of aircraft at their points of minimum separation, and an estimate of the position prediction error covariances at those points. Although the CPE algorithm currently runs in real time in CTAS, the statistical testing was done by post-processing data recorded with CTAS. The CTAS user can interactively adjust several parameters, such as the prediction time range and the criteria for data recording. A data record will be recorded only if the aircraft pair is predicted to come within the horizontal and vertical separation criteria selected by the user. The data records are recorded in an ASCII data file at a rate of one every 6 s for each aircraft pair that meets the criteria.

The raw tracking and flight plan data used for this paper came from the host computer at Denver Center (ZDV ARTCC) through a direct line to NASA Ames Research Center. That raw data was fed into CTAS to produce the prediction data. CTAS was configured to record data for level flight only, for minimum predicted horizontal separations up to 10 nmi, and for altitude separations up to 5000 ft. The data recording was typically started in the morning and stopped in the afternoon of the same day, for a total recording time of approximately six to eight hours each day. The resulting CTAS output file for each day was typically on the order of 50-100 MB in size. The data are recorded for each aircraft pair approximately once per 6 s. Each data record corresponds to a single aircraft pair at single point in time, and includes the following fields:

- aircraft identifications
- current time
- current positions/altitudes
- current ground-speeds/headings
- indication whether on or off flight plan
- predicted time of minimum separation
- predicted minimum horizontal separation
- predicted positions/altitudes at min separation
- predicted ground-speeds/headings at min sep.
- predicted times of top of ascent/descent

The aircraft are determined by CTAS to be on their flight plans if they are within 8 nmi (cross-track) of the planned flight-path, otherwise they are considered off their flight plans. These prediction data are the basic inputs to the CPE algorithm.

Data Processing

To test the acuracy of the CPE algorithm, the data are categorized according to specified parameters, then the expected conflict rate is compared to the actual conflict rate for each category. The primary categorization parameters are prediction time, path crossing angle, and computed conflict probability. The expected conflict rate is simply the average of the computed conflict probabilities for each category. If N is the number of prediction data records in a particular category, the expected and actual conflict rates are

$$P = \Sigma^i p_i / N$$

$$C = \Sigma^i c_i / N$$

where p_i is the computed conflict probability for record i (0-1) and c_i is conflict boolean for record i (0 or 1). The error or difference between the expected and actual conflict rates is then

$$E = C - P$$

Although the processing could have been done in a single step, it has been divided into three steps so that parameters can be varied without having to rerun the computations that are independent of those parameters. The three processing steps will be referred to as indexing, accumulation, and tabulation. Each step is implemented as a program written in C++ and run on a Sun workstation, and the output file from each program (except the last) is the input file for the next. All data files are in ASCII format. These programs are explained in the following subsections.

Indexing

The indexing program simply reads each record in the CTAS output data file, filters out those records for which the predicted altitude separation (at minimum horizontal separation) is less than 2000 ft, and writes the remaining records out to another file with an aircraft pair index appended to the end of each record. The indexing program is computationally intensive because it requires the construction of an aircraft pair list and, for each data record, searching through the list to find the matching aircraft pair. For the quantity of data used in this paper it takes approximately 80 minutes to run on a Sun Ultra 1. It needs to be done only once, however, and it greatly reduces the searching required in the next processing step, accumulation. Because the accumulation program may have to be run many times with different parameters to calibrate the error model (and to develop the software), this improved efficiency is important.

Accumulation

The accumulation program reads the files produced by the indexing program, accumulates a data summary for each aircraft pair, and writes the summaries to an output file. It also filters the data to eliminate any remaining cases of non-level flight, altitude separations less than 2000 ft, encounters involving aircraft off their flight plan, and other deviant cases. The accumulation program is a two-pass procedure and, for the quantity of data used in this paper, takes approximately 40 minutes to run on a Sun Ultra 1.

In the first pass, the input file is read from start to finish and several values are accumulated and stored for each aircraft pair. These values include a count of the number of data records for each pair and the minimum and maximum excursions of the predicted and actual heading, speed, and altitude. More importantly, the "truth" reference state at the point of minimum separation is determined by reading through the data to find the record in which the current time is closest to the predicted time of minimum separation (but not past it). At that time, the prediction time is so short that the positions, velocities, path angle and separation can be read and stored as the "truth" reference state at minimum separation.

In the second pass of the accumulation program, the data is read again from start to finish and each data record is tested and discarded if 1) the current time or the predicted time of minimum separation is before top of ascent or after top of descent, or 2) the current altitude is more than 1000 ft away from the true altitude at minimum separation, or 3) the path crossing angle is less than 15 deg. The first condition eliminates encounters involving one or both aircraft in ascent or descent, and the second condition eliminates encounters for which an unplanned altitude maneuver may have occurred. The third condition eliminates aircraft pairs with small path crossing angles, which are know to be difficult cases for CPE. Fortunately, for aircraft pairs with small path crossing angles, the encounters develop so slowly that CPE is not as important.

Each data record that passes through the filter then has its horizontal conflict probability computed based on the legal requirement of 5 nmi horizontal separation. The total prediction time range of 25 min is divided into 25 intervals of 1 min each, and an array of 25 elements is set up to accumulate the conflict probabilities for each interval. The computed conflict probability for each data record is summed into the appropriate element of the array, depending on the time to minimum separation. That conflict probability sum is the statistically expected number of conflicts for that interval. A second array of the same size is used to keep track of the number of records for each time interval so that the average conflict probability for each interval can be determined. A third array keeps track of how many records in each time interval predict a conflict (based on the 5 nmi horizontal separation criterion).

The output of the accumulation program is an ASCII data file with a one-line summary record for each aircraft pair. That record includes the following fields:

- aircraft identifications
- total number of data records
- path crossing angle at minimum separation
- minimum horizontal separation
- altitude separation at minimum separation
- data for each prediction time interval

where the data for each time interval includes:

- number of prediction data records
- number of records that predict conflict
- sum of computed conflict probabilities

Tabulation

The tabulation program reads the files produced by the accumulation program, sorts the data, and tabulates the results. For the quantity of data used in this paper, it takes only a few seconds to run. The predicted encounters are categorized according to three main parameters: prediction time, path crossing angle, and estimated conflict probability. For each category, the results are summarized in a single line of a tabular output format to be explained in the Results section to follow.

This categorization is necessary to properly test the algorithm. Without such categorization, it is possible that the conflict probabilities could be greatly overestimated for some types of encounters and greatly underestimated for others in such a way that the errors cancel and appear reasonable overall. Categorization of the results therefore minimizes the chances of mistakenly optimistic interpretations of the results. It is also potentially useful for calibration of the Gaussian error model, but that will not be pursued in this paper.

Results

CTAS prediction data was collected on over 9500 aircraft pairs over periods of six to eight hours on each of approximately 16 days at Denver Center (ZDV ARTCC). Data was recorded only for aircraft in level flight over FL290 and on their flight plan. The CPE procedure was tested only on aircraft pairs with path crossing angles of 15 deg or more.

This section is divided into two subsections. In the first subsection, the raw CTAS prediction error statistics are computed and presented, first in terms of trajectory prediction error, then in terms of conflict prediction error. In the second subsection the CPE accuracy is evaluated and presented.

Prediction Error Statistics

A prediction time range of 20 minutes was divided into 20 intervals of one minute each, and for each interval the mean, standard deviation, and rms position prediction errors were computed for the along-track and cross-track directions. The cross-correlations between the along-track and cross-track errors in each interval were also computed and found to be small, demonstrating that the principle axes are indeed the along-track and cross-track axes, as modeled. The mean errors were small compared to the rms errors, hence the standard deviations and rms values are virtually identical. The rms errors are plotted in Fig. 1. Also shown is the line that best fits the along-track rms error and the parabola that best fits the cross-track rms error.

The linear fit of the along-track rms error starts at 0.333 nmi for zero prediction time and increases at a rate of 0.223 nmi/min. These values are very close to the values of 0.25 nmi and 0.25 nmi/min, respectively, that were used in the prediction error model. The cross-track rms error was

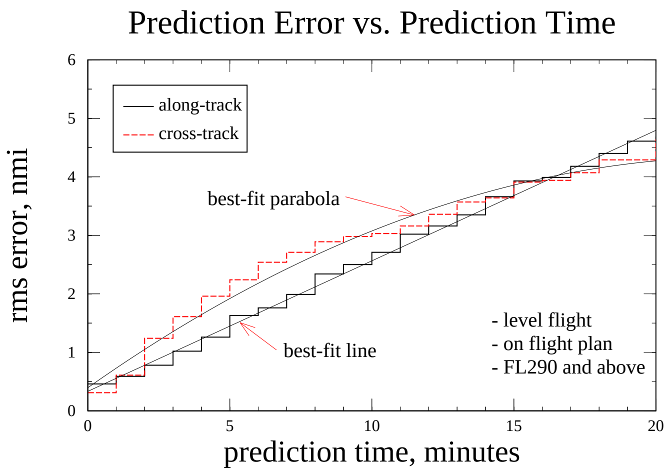

Figure 1: Position prediction error statistics

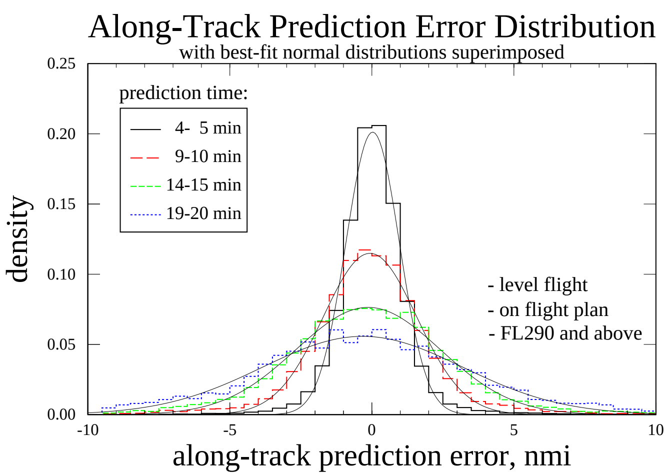

Figure 2: Position prediction error distribution

modeled as leveling off at approximately 2 nmi beyond 10 min, but it continued to increase to approximately 4 nmi at 20 min. For aircraft equipped with an FMS, the cross-track error would be significantly less, but such aircraft cannot be identified with the current form of the data records (this could change in the future).

The distributions of the errors were also computed and are plotted in Fig. 2 for one-minute increments of prediction time ending at 5, 10, 15, and 20 minutes. Empirical distributions must be approximated with discrete bins, and a bin size of 0.5 nmi was used here, hence the distribution curves are shown in steps of that size (to preserve the raw empirical form of the results rather than distort them for a smoother appearance). The best-fit normal (Gaussian) distribution curves are superimposed for reference. The remarkable closeness of the empirical results to normal distributions corroborates the choice of a normally distributed error model for the CPE algorithm.

The final prediction error statistics considered are the missed and false conflict alert rates. Recall that each prediction data record corresponds to one aircraft pair at one point in time and predicts the minimum separation of that aircraft pair. Conflicts and predicted conflicts are defined here simply in terms of the legal horizontal separation requirement of 5 nmi (with altitude separation ignored). If the *predicted* minimum separation is less than 5 nmi, that record is considered a predicted conflict, and if the corresponding *actual* minimum separation is less than 5 nmi, the record is considered to correspond to an actual conflict. The missed alert rate is the percentage of records that correspond to actual conflicts but were not predicted conflicts, and the false alert rate is the percentage of predicted conflicts that did not correspond to actual conflicts.

In practice, controllers can easily *decrease* the missed alert rate by using a separation alerting criterion greater than 5 nmi, but that will also *increase* the false alert rate. Hence, the results to follow are for reference only and are *not* intended to represent what controllers actually see in practice using CTAS (see [4] for those results). Note also that the missed and false alert rates are are only meaningful if the sample space is representative of the types of encounters controllers will see in practice, hence the 2000-ft altitude shift is not appropriate because large-angle encounters are overrepresented. Hence, only the 4000-ft altitude shift is used here (see the “Altitude Shifting” section for an explanation).

Figure 3 shows the missed and false alert rates categorized by prediction time in intervals of 5 minutes. Both rates increase with increasing prediction time, as expected, because predictions further into the future are obviously more difficult. Figure 4 shows the missed and false alert rates categorized by path crossing angle in arcs of 30 deg. Both rates increase with decreasing angle, again as expected, primarily because relative position error is more sensitive to relative velocity error for small path crossing angles. Figure 5 shows the missed and false alert rates categorized by estimated conflict probability in bins of 20 percent. Both rates start very high for low probabilities and decrease to very low values for high probability. The high missed alert rate for low conflict probabilities is not surprising, because the predicted minimum separation must be high for the conflict probability to be low. Note, however, that this high missed alert rate applies only to a very small number of actual conflicts in this low-probability category.

Figures 3-5 must be interpreted very carefully. As explained earlier, they are for reference only and are not intended to represent what controllers will actually see in practice using CTAS. Controllers can trade missed alerts for false alerts by simply adjusting their separation alerting threshold or their conflict probability alerting threshold. Typically, they want a low false alert rate for strategic, long-term predictions and a low missed alert rate for tactical, short-term predictions, so the alerting threshold can be a function of prediction time. The high missed and false alert rates shown in Figures 3-5 are not the fault of CTAS but are rather an unavoidable consequense of current practices in flight control and the state of the art in

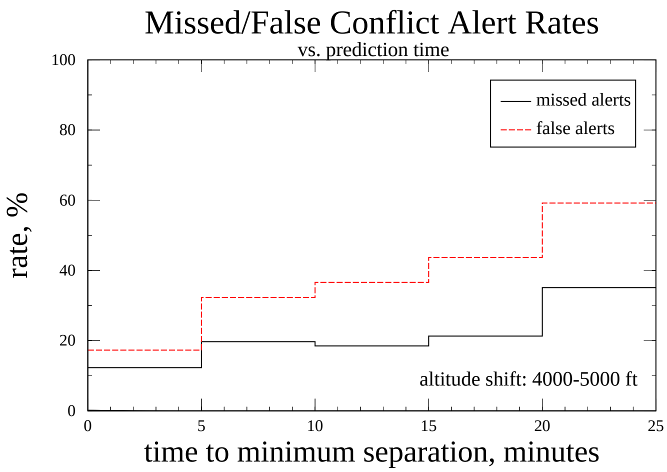

Figure 3: Missed/false conflict alert rates categorized by prediction time

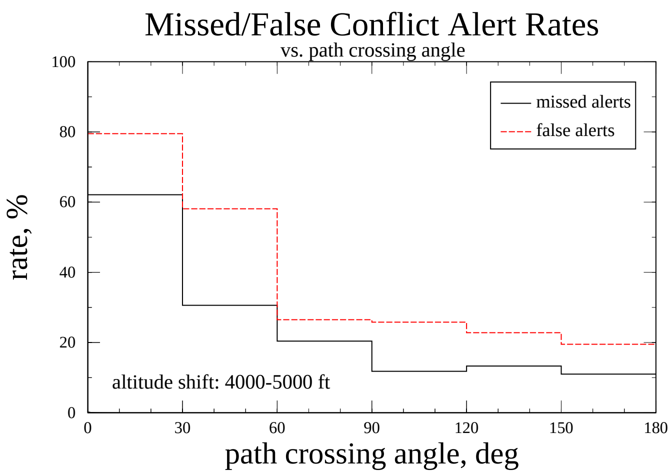

Figure 4: Missed/false conflict alert rates categorized by path crossing angle

wind modeling and prediction. In fact, these results illustrate the need for CPE.

CPE Accuracy

The results to be presented in this subsection are based on the default normally distributed (Gaussian) prediction error model for cruise that is currently in place in CTAS: the along-track rms error starts at 0.25 nmi and grows at 0.25 nmi/min; the cross-track rms error is 2 nmi. No accounting is done for aircraft type or for the availability of an FMS, and no effort was made to calibrate the parameters of the error model based on results of this study. Also, no wind-error cross-correlation model was used, which particularly affects encounters with a small path crossing angle. Lots of room for improvement remains, therefore. The results presented are merely intended to demonstrate the basic feasibility of CPE rather than to show its ultimate performance potential.

The main results are presented in Tables 1 and 2 for

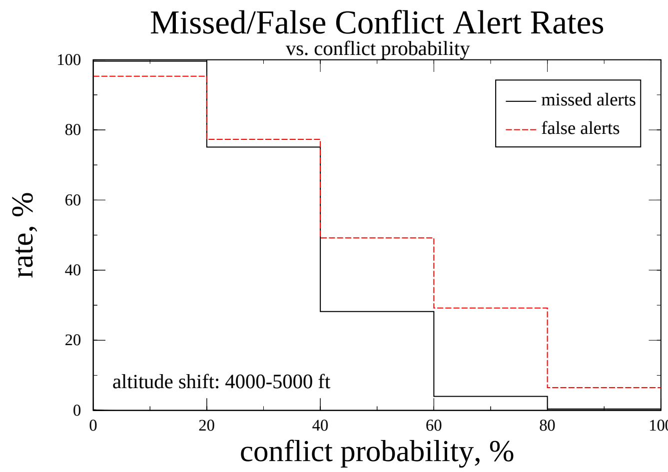

Figure 5: Missed/false conflict alert rates categorized by conflict probability

the 2000-ft and 4000-ft altitude shifts, respectively (see the "Altitude Shifting" section for an explanation). Each line in each table corresponds to a particular category of predicted encounter. The first three columns of each table specify the ranges of prediction time, path crossing angle, and estimated conflict probability, respectively. These three columns specify the category of predicted encounter. The fourth column of each table gives the number of aircraft pairs sampled in the corresponding category.

A brief explanation of the numbers of aircraft pairs in the fourth column will help prevent confusion. The number of pairs for the shortest prediction time interval (not shown) is equal to the overall number of pairs, and the number decreases with increasing prediction time because some aircraft pairs were not tracked, or did not adhere to their flight plan, for the full prediction time horizon. (If an aircraft deviates from its flight plan, all its previous data is discarded.) When the data is sliced by path crossing angle, on the other hand, the number of pairs adds up to the overall number because each pair has a unique path angle. However, when the data is sliced by conflict probability, the numbers of pairs adds up to more than the overall number because each pair can be in a different probability bin at different times.

The seventh and eighth columns give the expected and actual conflict rate, respectively, expressed as a percentage of the number of prediction records (*not* as a percentage of the number of aircraft pairs). The expected conflict rate is based on the CPE results. The final column gives the difference between the expected and actual conflict rate, expressed as a percentage of the total number of prediction records. This final column gives the ultimate measure of the accuracy of the CPE procedure.

Table 1 shows selected results for the 2000-ft altitude shift. The first line of data shows that the actual number of conflicts was within 0.5% of the expected overall number. The next section shows the results categorized by estimated conflict probability. The last column in this section shows that the CPE procedure works reasonably well, with a worst-case error of -11.5% for conflict probabilities of 20-40%. The next major section (marked by double lines) categorizes the results by path angle in increments of 30 deg. The expected and actual conflict rates match within 10% for every category except 30-60 deg, but even there they match within 15%, even though the number of aircraft pairs is fairly small. The last major section categorizes the results by prediction time in increments of 5 min. The expected and actual conflicts match well in all categories except perhaps the last, where the difference is 10.4%.

Table 2 shows selected results for the 4000-ft altitude shift. The total number of aircraft pairs is less than 1/10 of the number for the 2000-ft altitude shift because, as explained in the section on "Altitude Shifting," the number of pairs in high-angle encounters is much less. The first major section shows the results categorized by estimated conflict probability. The last column in this section shows that the CPE procedure works reasonably well for all categories except the 20-40% range, where the error is -18.8% for some unknown reason. The next major section categorizes the results by path angle in increments of 30 deg. The expected and actual conflict rates match reasonably well in most categories, given the fairly small number of aircraft pairs, but the performance needs some improvement. The last major section categorizes the results by prediction time in increments of 5 min. The expected and actual conflicts match reasonably well in most categories, but again needs some improvement.

Conclusion

Conflict probability estimation (CPE) is currently used in CTAS to determine when to notify air traffic controllers of a potential conflict. In this paper, the feasibility of CPE has been demonstrated, and the accuracy has been evaluated, for level flight using recorded air traffic data. The expected and actual number of conflicts matched reasonably well for most categories of predicted encounters and matched acceptably well for all categories, though the performance could still be improved in some areas. In the future, the stochastic error model on which the CPE algorithm is based can be calibrated and refined to improve the accuracy, particularly for small path crossing angles. The test procedures developed for this paper will later be applied to non-level flight. Eventually, the CPE procedure will be applied to conflict resolution and will be key to determining both when and how to optimally resolve potential conflicts.

References

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Table 1: Selected results for 2000-ft altitude shift

pred. time	path angle	conflict prob.	aircraft pairs	conflict rate actual	conflict rate expected	conflict rate diff.
min	deg	%	#	%	%	%
0-25	15-180	0-100	9511	45.9	46.4	-0.5
0-25	15-180	0- 20	4040	7.4	7.5	-0.1
		20- 40	2582	18.1	29.7	-11.5
		40- 60	2323	48.2	50.2	-2.0
		60- 80	2593	78.7	70.5	8.1
		80-100	2950	90.0	88.5	1.5
5-25	30- 60	40- 60	97	35.4	48.0	-12.6
		60- 80	48	54.8	69.7	-14.9
		80-100	30	80.8	91.1	-10.3
	60- 90	40- 60	95	54.0	49.3	4.7
		60- 80	75	78.8	69.6	9.2
		80-100	46	97.0	88.6	8.4
	90-120	40- 60	170	55.8	51.2	4.6
		60- 80	168	78.4	70.6	7.8
		80-100	123	95.2	88.1	7.1
	120-150	40- 60	499	46.1	50.3	-4.2
		60- 80	605	75.5	70.6	5.0
		80-100	508	89.9	87.1	2.8
	150-180	40- 60	1452	48.6	50.2	-1.6
		60- 80	1693	80.1	70.6	9.6
		80-100	2238	89.8	88.8	1.1
5-10	30-180	40- 60	1079	48.7	50.5	-1.7
		60- 80	1264	74.7	70.7	4.0
		80-100	2023	89.0	88.4	0.6
10-15		40- 60	764	47.5	49.9	-2.4
		60- 80	961	76.3	70.3	6.0
		80-100	1234	83.7	88.0	-4.3
15-20		40- 60	608	49.3	49.8	-0.5
		60- 80	639	75.0	70.2	4.8
		80-100	742	80.9	88.3	-7.4
20-25		40- 60	373	49.2	50.1	-1.0
		60- 80	290	75.9	70.4	5.5
		80-100	354	78.1	88.5	-10.4

Table 2: Selected results for 4000-ft altitude shift

pred. time	path angle	conflict prob.	aircraft pairs	conflict rate actual	conflict rate expected	conflict rate diff.
min	deg	%	#	%	%	%
0-25	15-180	0-100	904	29.7	37.0	-7.3
0-25	15-180	0- 20	535	1.7	7.0	-5.3
		20- 40	384	11.5	30.3	-18.8
		40- 60	252	44.3	49.5	-5.1
		60- 80	186	69.9	69.6	0.3
		80-100	161	93.3	89.1	4.1
5-25	30- 60	40- 60	90	35.1	47.8	-12.7
		60- 80	37	55.1	69.8	-14.7
		80-100	21	84.5	91.6	-7.1
	60- 90	40- 60	74	58.2	49.5	8.8
		60- 80	56	79.0	69.6	9.4
		80-100	32	97.7	88.2	9.5
	90-120	40- 60	23	62.4	53.0	9.4
		60- 80	23	70.1	69.9	0.2
		80-100	14	100.0	89.7	10.3
	120-150	40- 60	18	51.9	51.8	0.1
		60- 80	17	79.5	68.6	10.9
		80-100	18	80.7	87.9	-7.2
	150-180	40- 60	38	30.0	50.1	-20.1
		60- 80	50	67.9	69.9	-2.0
		80-100	72	94.3	89.3	5.0
5-10	30-180	40- 60	100	41.8	50.7	-8.9
		60- 80	102	62.6	70.8	-8.2
		80-100	88	91.4	87.7	3.7
10-15		40- 60	100	40.2	50.0	-9.8
		60- 80	70	73.8	66.2	7.6
		80-100	35	84.2	88.4	-4.2
15-20		40- 60	95	50.7	47.3	3.4
		60- 80	17	52.0	69.4	-17.3
		80-100	21	93.8	89.4	4.4
20-25		40- 60	28	55.7	45.9	9.8
		60- 80	3	66.2	72.1	-5.9
		80-100	9	93.9	88.2	5.7