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A STUDY ON SAFETY ASSURANCE FOR INCREASINGLY AUTONOMOUS TRAFFIC FLOW MANAGEMENT SYSTEM

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Abstract

An increasingly autonomous (IA) system is one that incorporates more automation and/or autonomous functions than are in use today, but are not yet fully autonomous. The authors identify the safety requirements and the changes necessary in systems safety assurance methods and system architectures to account for the reduction, change and/or elimination of the human roles in the IA system, through machine learning from simulated and predicted flight trajectory data. The approach of this study has two steps. First, the simulated flight trajectory data and the trajectory prediction made by NASA's computer system are used to train an algorithm to identify when, where and how the maneuverings due to traffic management initiatives (TMI) occurs. This step has more meaning when people deal with the real world data where the explicit information about TMI is not available. The second step is to analysis the prediction error with/without maneuverings due to TMI. The prediction error is defined as the difference between the predicted trajectory and the simulated actual trajectory in the directions defined as along the track, across the track, and in altitude.

1 Introduction

An increasingly autonomous (IA) system is one that incorporates more automation and/or autonomous functions than are in use today, but are not yet fully autonomous. Refer to [1] for more information about the IA system. The IA systems for aircraft, air traffic management (ATM) and other ground-based tasks are expected to be significantly safer, more reliable, more efficient, more affordable, and/or capable of previously unattainable missions. However, the system safety assurance methods and system architectures, which account for the reduction, change and/or elimination of the human roles in the IA system, need to be investigated. We focused on the safety assurance for IA system applied in the en route part of the traffic flow management (TFM).

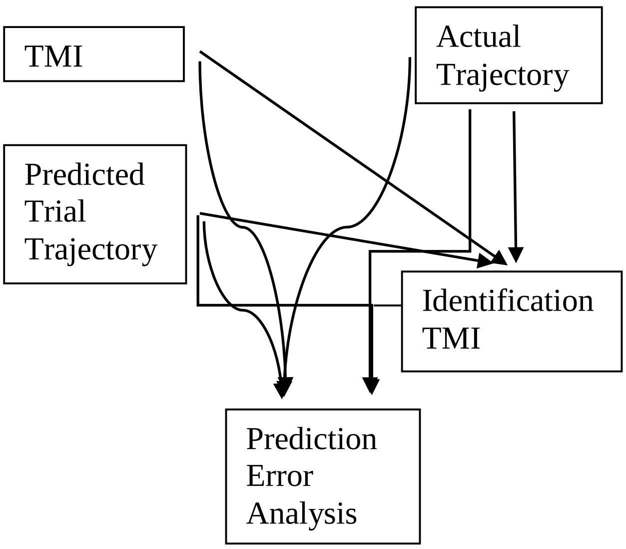
1.1 Data

We use two groups of data, one for developing the algorithm and the other for cross validation. Each data contains three parts, one is for actual flight trajectory, one is for predicted trajectory, and the other is for the TMI information. The data for true trajectory record the flight status every 5 seconds. The status includes altitude, longitude, latitude, air speed, heading direction, air craft type, airline, and so on. The predicted trajectory is calculated based on the current flight status, and predict for 30 minutes ahead, record the predicted status of the flight every 5 seconds. The predictions updated every 60 seconds. The data for TMI record the flights that involved, the maneuvering request type and the time the requests were sent out. Although the actual trajectory data in this study is not real world data but simulated data, based on how predicted trajectories are obtained, it does not sabot our purpose. To apply the algorithm, we developed in this study to real data is our next step of research. For real world data, we could have actual trajectory data, predicted trial trajectory data, but we will not be able to have the TMI information data explicitly in most situations. This makes the algorithm developed for identifying maneuverings in flights due to TMI necessary to analyze the prediction errors in real world data.

1.2 Approach

To study the safety assurance of the IA system, we need to know the performance of the prediction algorithm/system. We found that most of the prediction errors with large absolute values occur when there are maneuvering as suggested by traffic management initiatives (TMI). With simulated data as what we have now, it is not hard to distinguish these errors from all the others. Then we will be confident to use the significantly smaller value for the prediction error (without TMI) to make decisions such as whether it is necessary to send out a TMI due to the computer based prediction. If we do not remove the influence in prediction errors from the maneuvering due to TMI, the estimated value of the prediction errors will be significantly larger. Consequently, the IA system will be very inefficient in airspace usage, sometimes even not possible to work.

Therefore, identifying maneuverings due to TMI from actual trajectory and prediction data and analysis of prediction errors related to or not related to the maneuverings due to TMI are the two main task of this paper. These result will be the base for further study. The approach of this research is illustrated in below:



It means that we will use actual trajectory data, predicted trial trajectory data and TMI data to construct identification rules for identifying TMI in flight. And the prediction error analysis will be done in two ways: first, assume that we have TMI information, which is easier; second, we will assume that we do not have TMI information, and use identification rules to divide the prediction errors into two part, with TMI and without TMI. The results by two ways will be compared.

In the next section, we will discuss the TMI identification in details, and the prediction error analysis will be given in section 4. In section 5, discussions on the results we found and further researches are given.

2 Identify Maneuvering due to TMI

We consider twelve different types of maneuverings due to TMI in this paper. They are:

Type 1: During initial climbing, ask the aircraft to level at some altitude for a while and then climbing to its level flight altitude.

Type 3: During level flight, ask the aircraft to climb 1000 feet and stay at that altitude for a while and then descend to its original altitude.

Type 4: During level flight, ask the aircraft to descend 1000 feet and stay at that altitude for a while and then climb to its original altitude.

Type 5: Change course.

Type 7: descend to some altitude and then level flight for a while.

Type 8: Accelerate.

Type 12: Change course.

Type 13: Change course.

Type 15: Keep current status.

Type 16: Change speed.

Type 17: Change course.

Type 26: Change course.

Due to the natural of the different types of maneuverings, the identification algorithms are different. We separate them into altitude, direction, speed and unidentifiable categories.

2.1 Altitude Maneuverings

In flight, the aircraft usually first climbs, then levels off and cruises at some altitude, then descends. Therefore, the change in altitude itself is not sufficient to be a signal for locating this type of maneuvering.

Comparing the altitude change in flight without and with TMI, we found that it is necessary to divide the flight into climbing, level flight, and descending parts. Once we can do this, we will be able to tell whether there is any "unusual" maneuver in altitude, and these unusual ones very likely are due to the TMI.

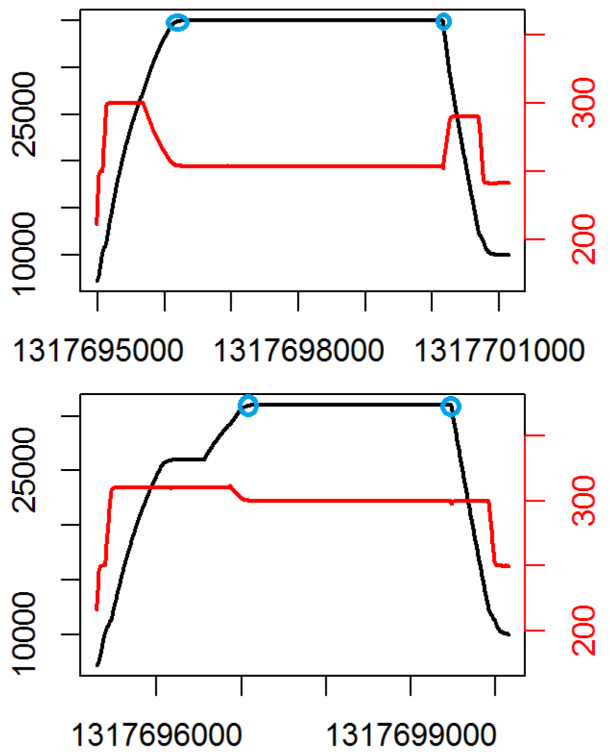


Fig. 1.: This figure shows a typical pattern (upper) of altitude (in black) and speed (in red) and a pattern with type 1 TMI (lower) of altitude (in black) and speed (in red). The horizontal axis represents the time and use second as unit. The vertical axis on right marks the altitude and use feet as unit, while the vcertcal axis on left marks the air speed and use knot as unit. The blue circles indicate where the climbing stops and level flight begins or the level flight ends and descending starts. Denote these points as LS and DS

To divide the flight into three parts, we need to locate the points marked by blue circles in Fig. 1. Notice that these points cannot be identified by change point identification methods in time series analysis, since the series are too "smooth" to be analyzed by general time series algorithms. Due to that there's no explicit information about which points are the "change" points, to find them is an unsupervised learning. The learning process is illustrated in below:

Calculate the 5 second difference in altitude
⇩
Locate the points with sign changes in difference Denote the set of these points by {CP}
⇩
Choose LS and DS from {CP}

The first and second steps are straight forward, while the third step need to distinguish whether the altitude difference in 5 second is due to random "bumpy" or "intentional maneuvering". This is a unsupervised machine learning task and the typical solution relies on the cluster analysis of the difference data.

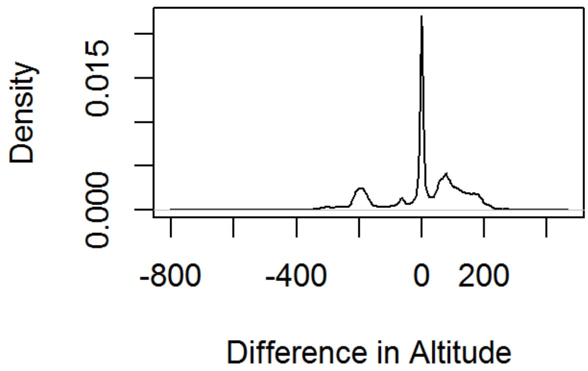


Fig. 2.: Empirical Probability Density of the Difference in Altitude.

It is not hard to see that there are 4 modes in the density. The highest mode almost symmetrically around 0 can be explained as the random "bumpy". The positive mode can be explained as the average altitude change in 5 seconds when there is intentional climbing. By eyeball, this mode locates around 75, which corresponds to climbing 900 feet per minute. Look at the plot more carefully, we can see that the density curve is quite flat on the right hand side of this mode and then dropping rapidly when greater than about 180, which corresponds to climbing about 2200 feet per minute. On the negative side, there are obvious two modes. The one around -50, corresponds to descending 600 feet per minute, while the one centered at -200, corresponds to descending about 2500 feet per minute.

To formally find the mean and standard deviation of difference in altitude around each mode, we apply classical k-mean method and Bayesian nonparametric method to this data. The result from k-mean study is:

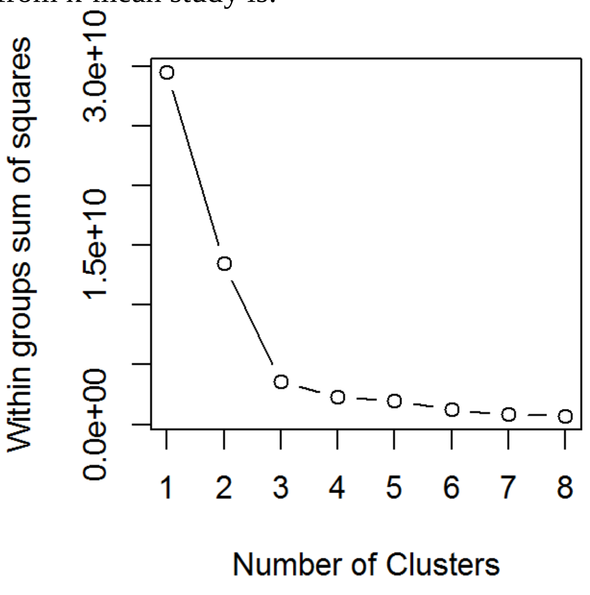


Fig. 3.: Choose number of clusters based on the change of sum of squares within groups.

By the rule of cluster analysis, we are in favor of choosing 3 clusters, which is different from what we saw by eyeball and different from what we would like to see based on our prior knowledge on aviation. Mathematically, this is due to the fact that the k-mean method is under Gaussian distribution assumption. However, for identifying LS and DS purpose, 3 clusters could be sufficient to distinguish the "intentional" and "unintentional" altitude change. The completed cluster analysis result is listed in the table below:

Table 1.: Cluster Analysis for Altitude Change

Num. of Clusters	Cluster Center	Mean	Std. Dev.	Num. of Data
3	1	1.09	31	936035
	2	126	46	677187
	3	-208	58	355555
4	1	131	44	616583
	2	-215	55	325428
	3	-78	30	135292
	4	13	25	891474
5	1	-313	61	56683
	2	-6	23	802105
	3	81	22	506667
	4	-186	31	304576
	5	169	32	298764

Based on the table above, we can conclude that the 5 cluster is a better fit for this data and for our purpose. Although the estimation of each groups show some biasness, the separation of the clusters is significantly better than the models with only 3 or 4 clusters. By the direction of the biasness, we can see that the biasness came from the extreme values in raw data, which somehow violated the Gaussian assumption. Refer to [2] for more technical details.

The conclusion is: when the change in altitude in 5 seconds between -120 to 40, then it is unintentional altitude change, otherwise intentional. Now we have,

$$P(\mathrm{IA}|\mathrm{UA}) = 0.025\,,$$

$$P(\mathrm{UA}|\mathrm{IA}) = 0.05\,,$$

Where IA denotes the intentional altitude change, UA denotes the unintentional altitude change, and $P(\mathrm{IA}|\mathrm{UA})$ denotes the probability that an unintentional altitude change being identified as intentional altitude change. We keep the probability of unintentional maneuvering being identified as intentional maneuvering even lower than the opposite error in order to achieve the more conservative result, which in turn means safer rules.

Equipped with the above rules for distinguish intentional and unintentional altitude change, we are able to find the LS and DS points and later identify the Type 1, 3, 4 and 7 TMI during flight. The identification results are summarized in the table below:

Table. 2. Identification Result for Altitude Maneuverings.

	Type			
	1	3	4	7
Missing Rate	0.031 (0.034)	0.067 (0.065)	0.062 (0.060)	0.001 (0)
False Rate	7.6e-6 (9.1e-6)	0 (0)	0 (0)	1.9e-6 (1.2e-6)

Missing rate denotes the ratio that the number of TMIs that are not identified versus the total number of the TMI in the data. It is not surprised to see that the rate on average is almost the same but a bit higher than P(UA|IA), since there're more criteria to be satisfied to be identified as a TMI. The false rate denotes the number of the identified TMI's that does not exist versus the total number of the time points with non-zero altitude change. The false rate are significantly less than the P(IA|UA), which is around 0.025. This is also because of to be identified as a TMI, while it is not, many more conditions need to be satisfied. Therefore, the false rate is dropped to almost zero.

The upper number in each cell are the ratio calculated based on the training data set, while the lower numbers in brackets are calculated based on the data for cross validation.

The ultra-goal of this research is to quantify the prediction error. Therefore, the acceptable low rate of missing identification combined with the almost zero false positive rate, is what we want.

The following subsections follow the same identification logic. Hence, similar discussion will be omitted.

2.2 Direction Maneuverings

Compared to other types of maneuverings, direction maneuverings are quite obvious to be identified. However, direction maneuverings cannot be identified by trajectory data itself only. The predicted trial trajectories are needed.

To identifying this type of maneuverings, supervised and unsupervised learning techniques are both applied and compared. The unsupervised study is similar to the one in previous sub-section. The detail is omitted here. The unsupervised study is a classical logistic regression, due to the fact that these type of TMI normally with time lag very short, such as 10 seconds, unlike the time lag in type 1 and 7, which vary a lot, from a couple of seconds to more than 10 minutes. The uncertain length of time lags makes it very difficult to subtract the "feature" from the data for supervised study.

Other than the above two, the typical patterns of these types of TMI maneuverings and the pattern for one common situation that also introduces large valued prediction direction errors can be distinguished relatively easily. Refer to the figure below:

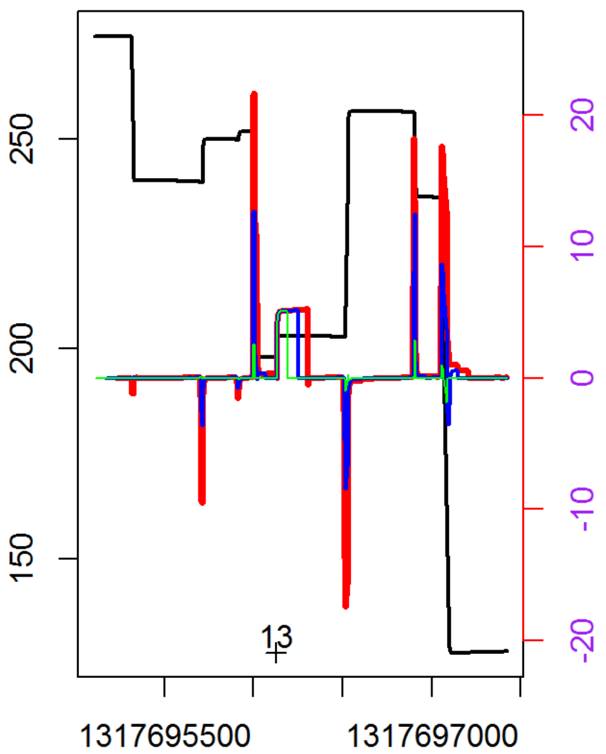


Fig. 4.: Pattern of Direction Maneuvering.

In the figure above, the cross marked with 13 shows the time spot when type 13 TMI was sent to the aircraft. The black folding line express the flight heading direction, which first flies to west then eventually turned to south east. The red, blue and green lines show the prediction errors in direction compared to the actual trajectory. The red line corresponds the prediction errors for 3-minute prediction, while the blue for 2-minute prediction and green for 1-minute prediction. The Y-axis on the left hand side marked with heading direction in degrees, and the Y-axis on the right hand side marked with the degrees for prediction errors in direction.

It is obvious that the prediction error related to TMI for heading direction has “flat top”, while the direction errors due to the usual turnings have “sharp top”. It is not necessary that the TMI maneuvering has larger valued prediction errors than the prediction errors for normal flight. These sharp large prediction errors are due to the earlier or later actual turning compared to the predicted time point for starting turning.

With all these being said, the identification results are summarized in the table below:

Table. 2. Identification Results for Direction Maneuverings.

	Type				
	5	12	13	17	26
Missing Rate	0.04 (0.04)	0.13 (0.11)	0.055 (0.031)	0 (0)	0 (0)
False Rate	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

From the table above, we can see that the identification of maneuverings due to these types of TMI is quite good.

2.3 Speed Maneuverings

Type 8 and 16 TMI’s belong to this category, which are the hardest ones to be identified, especially when Type 16 TMI occurs around the initial descending point, where the prediction of air speed around this point is very rough even without any TMI interruption. To see this, please refer to the figure below:

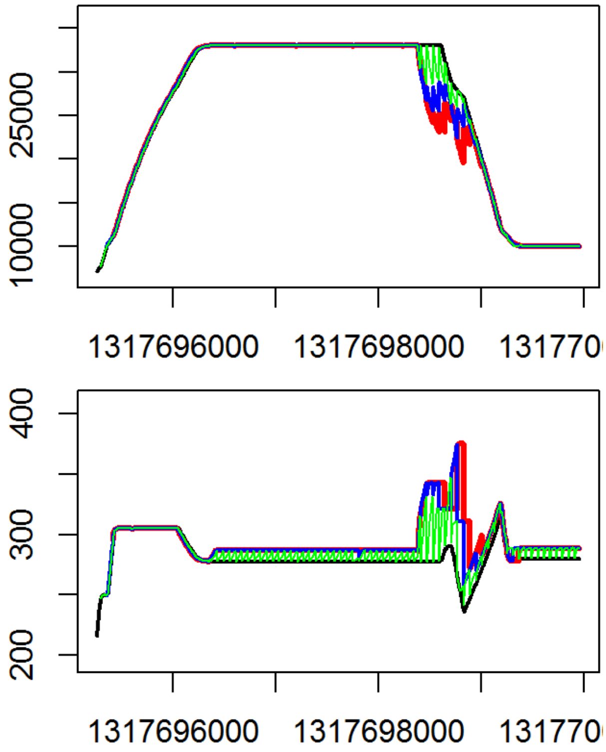


Fig. 5.: The top is the altitude of the flight and its prediction. The bottom is the air speed of the flight and its prediction.

It is not hard to see that the prediction errors related to the speed change in descending are large. The prediction error in speed also affects the prediction in altitude significantly. However, with or without TMI in speed during descending, the prediction errors around initial descending point are always large. Therefore, the first rule for identifying speed TMI is: do not rely on the prediction errors in altitude. Second, although the patterns of the airspeed are much noisy than other characters, it is still very helpful to compare the pattern to a typical pattern. Of course, in this situation, the typical pattern cannot be seen as often as other typical pattern for other values, such as altitude. Refer to Fig. 1., on the top part of the figure, there is a red line, which is the typical pattern for airspeed. Using the similar approach to locate the turning points at the ends of two flat part of the line is a key in identification.

The identification results for speed type TMI are summarized in the table below:

Table. 3. Identification Results for Speeds Maneuverings.

	Type	
	8	16
Missing Rate	0.34 (0.42)	0.41 (0.39)
False Rate	0.0001 (0)	0.0001 (0)

The speed type TMI is really hard to be identified without increasing the false rate. However, we still can achieve the low false rate. This means that we will not sacrifice the safety assurance when we use the prediction error results we have based on what we found from the identification to construct the new safety assurance rules for IA system.

2.4 Unidentifiable Maneuverings

Basically, the unidentifiable maneuverings are the ones that related to some TMI, but we cannot distinguish them from normal flight trajectory without TMI. In some situations, for example, type 15 TMI, which is basically "keep your current status", or some tiny small direction changes in direction type TMI, these unidentifiable maneuverings obviously will do no harm to the prediction error analysis. For some other situation, such as the ones described in subsection 2.3, it is not so obvious that the miss identification will not sacrifice the efficiency. Notice that, the unidentifiable actually means that the differences between actual trajectories and predicted trial trajectories have no significant difference between the ones relate to TMI and the ones do not relate to TMI. Hence, Treat the unidentifiable maneuverings as there were no TMI, actually does not increase the standard deviations, or average or extreme absolute values of the prediction errors.

3 Trajectory Prediction Errors

The prediction errors have been studied by Lauderdale et. al. [2]. In that paper, the authors emphasized on finding out which is the most significant source of the prediction errors in trajectory prediction. However, the TMI related maneuverings did not be studied then.

The prediction errors for a Δt prediction are defined as vectors from the predicted position at time $t+\Delta t$, where t is the current track time, to the true trajectory position at time $t+\Delta t$.

By the nature of flight trajectories, we project the vectors into three dimensions: parallel to the predicted trajectory in the horizontal plane (along-track), perpendicular to the predicted trajectory in the horizontal plane (cross-track), and in the vertical axis (altitude). Note that the definition of the error uses the predicted trajectory as the base instead of the "true" trajectory. This looks unusual, but has several benefits. First, for a real time system we are not able to get the "true" position for any future state, but knowledge about the probability distribution of the future position based on the prediction can be used to improve predictions. Second, it avoids confusion about the heading due to the possibility that there is a direction change in the near future. Also note that we define the along- and cross-track errors in a horizontal plane instead of a plane parallel to the trajectory. This brings mathematical simplicity to the data analysis and, by the nature of en route flight, the along and cross errors defined in parallel to the trajectory plane have very marginal difference to what we defined.

Table 4: Standard deviation with and without partitions.

Standard Deviation	Without TMI	With TMI
Cross track error	11.87 (11.92)	435.76 (435.75)
Along track error	66.55 (78.32)	267.45 (259.11)
Error in altitude	201.87 (220.28)	307.45 (289.72)

The above table shows the difference in prediction errors for trajectories with TMI influence or without. The value in the brackets are calculated based on the identification, while the other value is based on the "perfect" information.

The two groups of values are close to each other, which means our identification results is quite good for the purpose of analyzing prediction errors.

Based on the standard deviations calculated, we have the following two claims:
In average, the maneuverings due to TMI contribute significant amount errors to the prediction.

The relatively small shrinkage in standard deviation for errors in altitude, reflects the difficulty we discussed in sub-section 2.3.

The identifiable property for TMI related maneuverings and the significant shrinkage in prediction errors standard deviations while removing the influence from TMI, shows that these results are very helpful for construct the safety assurance for IA system.

5 Further Research

A straight forward improvement of this research can be done by using more sophisticated Bayesian nonparametric method to carry out the unsupervised learning in clustering the altitude differences and other similar values.

We have seen that the Gaussian assumption does not fit very well for our data, which induces biasness and rough estimation of number of clusters and the center location of each of the clusters. The Bayesian nonparametric methods are much more flexible, which does not rely on any particular assumption on probability distributions, but the continuity of the distribution and some mild tail properties on the distribution. Refer to [4] for more details on this method. However, the computation cost is very high. For example, a single run for a univariate value with about 0.5% of the total sample size will take about 6 hours on a computer with 6th generation i-7 CPU and 32 Gb memory.

To illustrate how this works, the author worked on a small subset of the altitude data for 10,000 MCMC steps. The plot for checking the convergence of the algorithm.

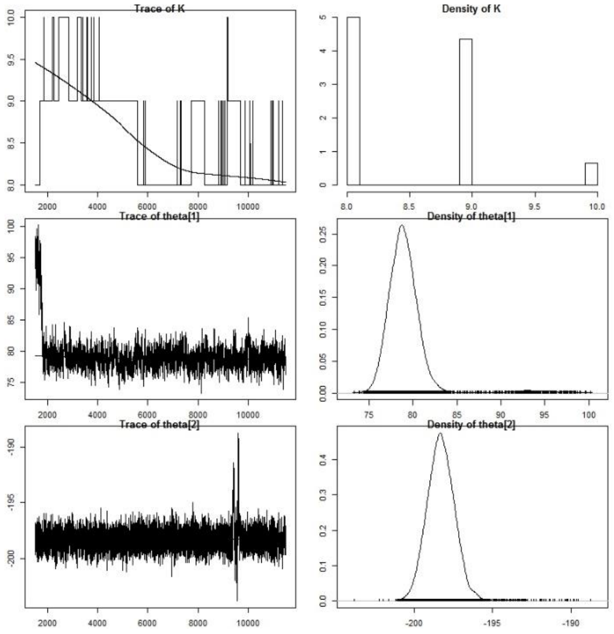


Fig. 6.: MCMC convergence check (part of the plots).

From the plot, we can see that the number of the clusters are not quite converges, which needs more steps (time) to run, or needs larger upper bound of the total number of the clusters. The location of the center of each clusters has converged. Therefore, although this Bayesian algorithm has not been tuned well, we can use its results do some comparison with the classical methods.

Although not quite converged, the estimation of the number of the clusters is 8.79 with standard deviation 1.03. This is much more than what classical method suggested. Considering the fact that the Bayesian nonparametric methods almost always over estimate the number of clusters, we should not be surprised here. The tricky point is that to achieve the flex shape of the distribution for each cluster, the Bayesian methods essentially use the mixture of several closely located distributions to represent one cluster. In this way, they can better catch the location of the center of the clusters and the shape of the distributions for these clusters. Of course, the variance or standard deviation of each cluster will have better estimation as well.

Look at the estimations for the center of the clusters: (the left column is the estimated value and the right column is the standard deviation.)

```
theta[1]    7.928e+01 2.833e+00
theta[2]   -1.983e+02 1.002e+00
theta[3]    2.168e+02 4.422e+02
theta[4]    2.517e+00 1.122e+00
theta[5]   -4.514e+01 2.703e+02
theta[6]   -9.479e-02 3.098e-02
theta[7]   -5.225e-03 8.698e-04
theta[8]   -2.659e+02 4.013e+00
theta[9]    1.531e+02 8.560e+01
theta[10]  -2.250e+01 3.801e+02
```

We can see that there are 3 centers around 0, with the largest has absolute value about 2.5 and the other two's absolute value way smaller than 1. This is better or at least as good as the classical estimation, which are 1.09, 13 and -6. There are another center around 79.82, another two around 216.8 and 153.1. All of them look closer to the empirical modes than the classical estimates. On the negative side, there are -198.3, -45.14 (with very large standard deviation 442.2), -265.9, and -22.5 (with large standard deviation 380.1). Such estimates already fit the data better, in the sense that their values are closer to the modes and their standard deviations reflect better the flatter part of the empirical density.

Therefore, we can conclude that the Bayesian nonparametric methods are promising for this research. Once we have enough resource to tune the algorithm, we should apply these methods.

Another study will be carried out on the correlation structure of the prediction errors. We only analyzed the prediction errors separately in one of the three dimensions. Nevertheless, there's correlation structure among them, as showed in the figure below:

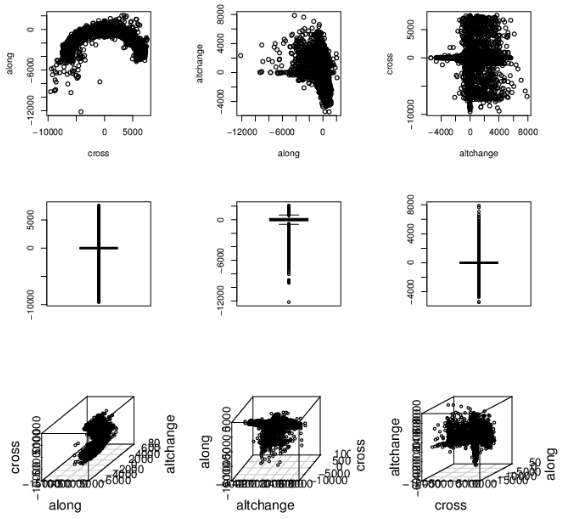


Fig. 7.: Correlations among prediction errors in three dimensions.

By studying the multivariate property of the prediction errors, we should be able to obtain more precise prediction errors, which in turn will let the airspace be used more efficiently.

The ultra-goal of prediction analysis is to estimate a 3-D distribution of the errors. This work involves density estimation for big data. Therefore, the computation cost issue will be the barrier again.

The maybe most important further research is to apply the identification rules we found to the real world trajectory data. The real world data may have some properties we haven't noticed yet. Without studying on the real world data, all the results we have now are of limited meaning.

6 Summary

We constructed identification rules/algorithms to identify maneuverings due to TMI in flight with trajectory data. The identification is quite successful in the sense that most of the maneuverings with TMI have been identified with false rate almost 0.

We also analyzed the prediction error, with the full information about TMI and without such information. The results are similar, which again shows that our identification was successful.

Based on the findings in both identification and error analysis, we are at a stage ready to deal with the real world trajectory data, where information about TMI is not explicitly available.

Some issues in algorithms, computation and further study on prediction errors has been discussed.

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