

CONFORMANCE MONITORING APPROACHES IN CURRENT AND FUTURE AIR TRAFFIC CONTROL ENVIRONMENTS

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Introduction

Conformance monitoring is a core task in Air Traffic Control (ATC) operations to determine whether aircraft are adhering to assigned trajectories. This is important for many reasons, including to ensure that tactical collision avoidance maneuvers are properly executed; strategic conflict detection & resolution schemes are valid and security around sensitive locations is maintained.

In today's ATC environment, controllers monitor for conformance via radar systems that primarily provide positional information. As a result, non-conformance criteria are generally based on positional deviations from the assigned trajectory [1] or penetration of restricted airspace such as the No Transgression Zone (NTZ) on PRM approaches [2]. Future ATC surveillance systems such as Automatic Dependant Surveillance (ADS) should provide access to additional aircraft state information which could be used for more effective conformance monitoring. However, at present there is a lack of clear rationale for which states should be surveilled and how they would be used to enable conformance monitoring to be performed at a level appropriate for future operational requirements.

This paper describes a framework for this purpose that poses the conformance monitoring task as a model-based fault detection problem.

Conformance Monitoring as Fault Detection

The conformance monitoring task can be posed as a classic fault detection problem where non-conforming behavior of an aircraft is considered a "fault". Fault Detection and Isolation

(FDI) techniques can be employed to determine if observable aircraft states are consistent with normal (i.e. conforming) or abnormal (i.e. non-conforming) behavior.

Model-Based Fault Detection

Among the various strategies used in fault detection theory, model-based techniques have generally proven most capable [3,4]. Figure 1 shows the conceptual structure of a typical model-based fault detection scheme.

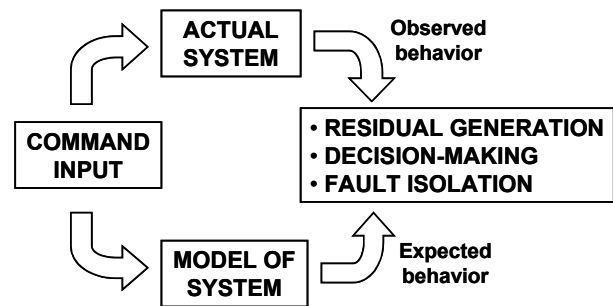


Figure 1: Model-Based Fault Detection Concept

A model of the actual system being monitored is used to develop the expected behavior given the command input and other knowledge of the system. The difference between the expected behavior based on the model and that of the actual system observed through a measurement system is quantified in a *residual*. The residual should be generated in such a way that the larger the difference between the observed and expected behaviors, the larger is the residual.

The *decision-making* function is then required to determine whether a fault exists or not based on

the characteristics of the residual. In the simplest form of decision-making, a fault is declared if the residual exceeds some pre-determined threshold. Although more sophisticated techniques are commonly employed to minimize false alarms (e.g. residual filtering, statistical and fuzzy decision making, pattern recognition, etc.), they all generally require some form of threshold test to declare the existence of a fault. However, since the model cannot provide a perfectly accurate and complete representation of the processes occurring in the actual system, challenges exist to distinguish effects observed in the residual due to modeling uncertainty from those due to real faulty/non-conforming behavior. Signal detection theory can be used to set thresholds based on false alarm/missed detection performance goals.

After a determination of non-conformance has been made, *fault isolation* techniques can be used to determine where the fault may have occurred. This also has potentially useful applications in context of conformance monitoring for “intent inferencing” to help determine potential reasons for non-conformance.

Model-Based Conformance Monitoring

Figure 2 presents the ATC conformance monitoring task in the model-based fault detection structure. The “Conformance Basis” block at the left is analogous to the command input and represents the baseline against which the conformance is monitored. The Conformance Basis is typically the currently-active set of clearances which are communicated to the flight crew of each aircraft.

Ideally, the flight crew receives the clearances and makes appropriate inputs to the aircraft systems (flight automation or manual control) to manage the aircraft trajectory in a manner consistent with the active Conformance Basis. These “Real World” processes are shown by the upper box in Figure 2. The “Conformance Monitoring Functions” block at the right receives observable real world states from surveillance systems and determines if the observed behavior is consistent with the expected behavior using FDI-inspired techniques of residual generation, decision-making and intent inferencing. The expectation is based on some “Conformance Monitoring Model” of the real world shown in the lower box.

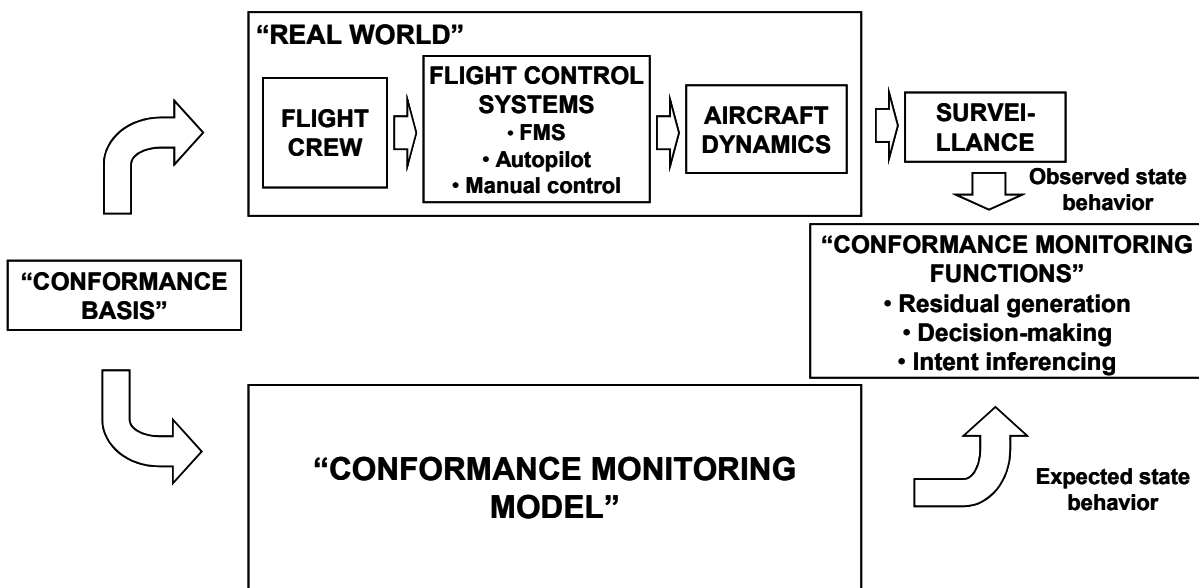


Figure 2: Model-Based Conformance Monitoring Concept

Conformance Monitoring Analysis Framework

In order to analyze the influence of different state surveillance environments on the conformance monitoring task, a Conformance Monitoring Analysis Framework has been developed using the model-based conformance monitoring concept. In order to help describe different surveillance environments, a general Surveillance State Vector, $X(t)$ has been defined [5] which supplements the traditional dynamic states of position, velocity and acceleration with “intent” states defining the future trajectory of the aircraft through current target, planned trajectory and destination states:

$$X(t) = \left\{ \begin{array}{l} \textit{Position, } R(t) \\ \textit{Velocity, } V(t) \\ \textit{Acceleration, } A(t) \\ \textit{Current target states, } C(t) \\ \textit{Planned trajectory, } T(t) \\ \textit{Destination, } D(t) \end{array} \right\} \quad \text{Eqn. 1}$$

This structure is consistent with the way intent states influence the dynamic states in the operational environment. Current target states are generated by the autopilot or manual control input to which the aircraft control systems are driven (e.g. autopilot target heading), while the higher level trajectory functions (performed by the FMS or pilot) generate future target states to manage the aircraft trajectory to the ultimate destination.

The Surveillance State Vector and model-based conformance monitoring concepts are integrated in the Conformance Monitoring Analysis Framework shown in Figure 3. The elements are discussed in more detail below.

Conformance Basis

The Conformance Basis can exist at the various defined levels of the intent state, including the current target state level (e.g. assigned heading, altitude or speed); trajectory level (e.g. Flight Plan, Standard Instrument Departure [SID] or Standard Terminal Arrival [STAR]); destination level (e.g. fly direct to airport A) or at some less structured level (e.g. descend at pilot’s discretion).

Real World Representation

In Figure 3 the “Real World” processes are represented by the key elements which are involved in executing the clearance or other instructions forming the communicated Conformance Basis. This is modeled as a classical feedback control representation of the aircraft control system supplemented with upstream flight crew and aircraft intent components. Each element in the representation generates appropriate control system target states for the downstream elements as shown by the downward arrows to the surveillance block, together with arrows defining characteristics of the modeled elements themselves. The surveillance block provides real world state observations to the Conformance Monitoring Functions block at the right.

Using this representation, it is possible to examine not only the effects on conformance monitoring of improved surveillance of the traditional dynamic states such as position, but also the effect of other states that help define the behavior at different points in the control representation, such as those shown by the downward arrows. The surveillance block of Figure 3 is represented slightly differently than in the general case of Figure 2 to illustrate this point more clearly.

Conformance Monitoring Model (CMM)

Conceptually, the states surveilled from the real world can be used to help populate the appropriate Conformance Monitoring Model elements which may mirror those that exist in the real world, as shown in Figure 3. There are many potential forms that the Conformance Monitoring Model could take, for example it could be a simple “mental model” of expected behavior in a controller’s mind [6] or a more explicit functional model implemented in a decision support tool. These latter types could exist at many different levels, for example as a high-fidelity model of the specific aircraft and environments being monitored or a simple point-mass model that captures only very general aircraft behaviors.

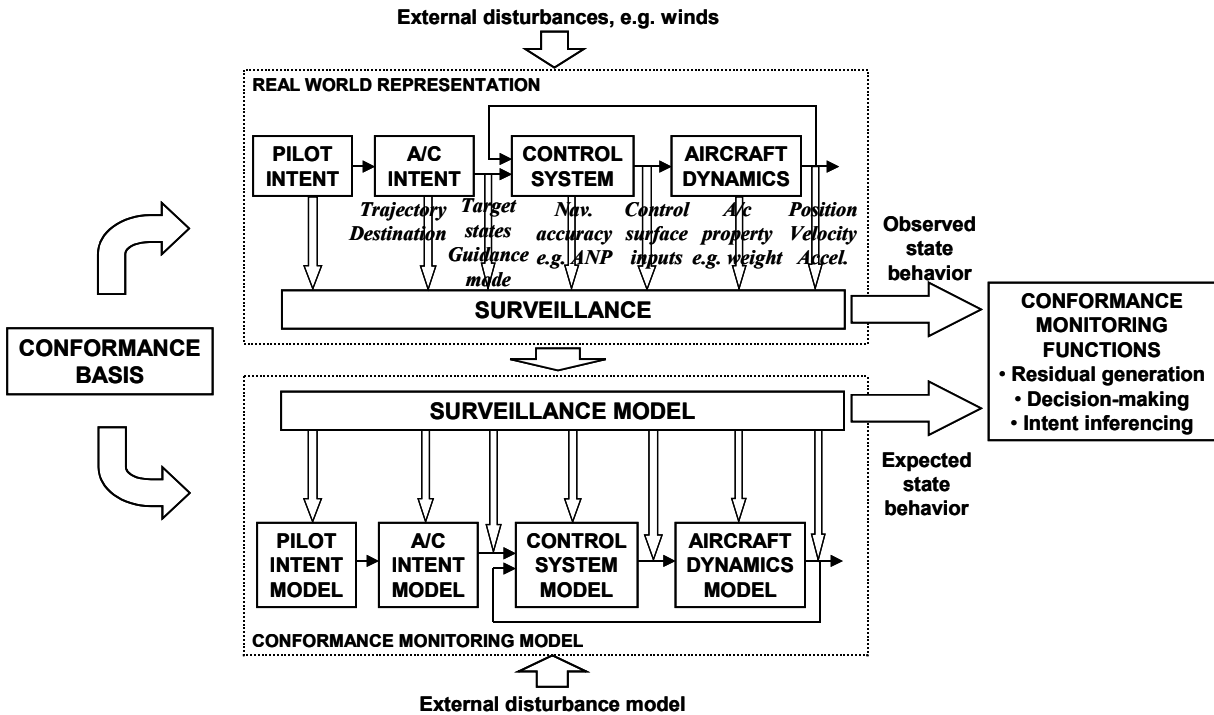


Figure 3: Conformance Monitoring Analysis Framework

One of the greatest challenges in this application is the development of the Conformance Monitoring Model at an appropriate level, i.e. with sufficient fidelity to undertake effective conformance monitoring, but not so detailed that modeling uncertainty and sampling issues introduce too much noise into the residual.

Observer-based approaches have commonly been used in fault detection applications to generate the expected behaviors (e.g. the maximum likelihood estimate from a Kalman filter [7]), but they require accurate mathematical models to be developed of the monitored system and noise sources. While the aircraft dynamic components can be modeled relatively well, the presence of unknown disturbances and the human control elements can lead to uncertainties in the model and sub-optimal estimates being output from the observer.

The pilot and flight automation elements in this problem are fundamentally different in character from the dynamic components, lending themselves more to real-time, simulation-based modeling approaches. Although models of the

various elements and noise characteristics are still required, engineering simulations of the key processes are often easier to implement.

Nevertheless, significant modeling uncertainty limits the performance of all the aforementioned ‘quantitative’ residual generation approaches. Under conditions where this exists, ‘qualitative’ techniques can be employed as well which only require the use of declarative (i.e. heuristic) information such as the sign, rate of change or relative magnitudes of observed variables. This approach to residual generation is relatively new and many investigations are currently underway, utilizing novel techniques such as fuzzy logic and machine learning [8].

In the conformance monitoring application, quantitative and qualitative residual generation techniques can be employed in parallel to take advantage of their complementary features. The qualitative notion of the signs and rates of change of observed states for an aircraft expected to be adhering to a certain Conformance Basis can be used in parallel with a quantitative technique that

would otherwise suffer unduly from modeling uncertainty.

Conformance Monitoring Functions

Residual Generation

The residual generation scheme should utilize as many states as required (or are available) to build up the best measure that describes whether the aircraft being monitored is behaving in a conforming fashion. One approach to this process is proposed here in terms of a ‘‘Conformance Residual’’, CR , defined as:

$$CR = \frac{\sum WF_x |x_{obs} - x_{CMM}|}{n} \quad \text{Eqn. 2}$$

where x is a useful observed state, WF_x is a weighting factor for each state, x_{obs} is the observed value for each state, x_{CMM} is the expected value of the state from the Conformance Monitoring Model (annotated as CMM) and n is the total number of states used to define the Conformance Residual.

Thus, the state components of CR add to the total in proportion to the magnitude of the difference between the observed and expected conformance behavior.

The weighting functions are used to normalize each state component to acceptable conforming behavior limits (i.e. a ‘qualitative’ technique) and to reflect each state’s relative importance. The concept of placing limits on acceptable deviations from assigned values is already well established. For example, the Required Navigation Performance specifications [9] define cross-track containment limits within which an aircraft must remain for 95% of the time to be RNP-compliant. As such, an aircraft’s RNP level or surveilled Actual Navigation Performance (ANP) is a reasonable basis for normalizing an aircraft’s cross-track position. Under this assumption, a cross-track weighting function would be the reciprocal of the RNP or ANP value. The philosophy of using 95% confidence containment limits as the basis for developing weighting functions can also be used for other states that might be observable. A weighting function that is the reciprocal of a suitable range

defining the 95% confidence containment interval (annotated as Δx_{limit}) is then appropriate.

The overall normalization of CR is desirable so that a comparison can be made between surveillance environments where differing amounts of state information may be available. This is achieved by simply dividing the sum of the various weighted components by the number of components used in the summation. As an example, the Conformance Residual for an environment containing surveilled position (from which cross-track position, L , can be determined), track angle (ψ), roll angle (ϕ) and track target state (ψ_T) information would be:

$$CR = \frac{\left[\frac{|L_{obs} - L_{CMM}|}{RNP_{spec}} + \frac{|\psi_{obs} - \psi_{CMM}|}{\Delta\psi_{limit}} + \frac{|\phi_{obs} - \phi_{CMM}|}{\Delta\phi_{limit}} + \frac{|\psi_{Tobs} - \psi_{TCMM}|}{\Delta\psi_{Tlimit}} \right]}{4} \quad \text{Eqn. 3}$$

It should be noted that other approaches to determining the Conformance Residual could also be used, which will be investigated in future work. For example a vector residual could be defined where each component of the vector is the difference between the observed and expected values of a state.

Decision-Making

Once the residual has been generated, the decision making process involves a determination of whether the residual behavior is characteristic of a conforming aircraft or not. The techniques used for this will depend on the metrics of interest (e.g. tradeoff of speed vs. accuracy of decision). Given the form of the Conformance Residual in Eqn. 3 with 95% confidence level as the normalization basis, a CR value of 1 implies that the average state deviation is at the 95% confidence level, presuming that the Conformance Monitoring Model is accurate and the 95% confidence state containment limits have been set appropriately. For example, in an environment where only position is used to establish conformance, $CR < 1$ implies an aircraft within its RNP containment limit, $CR = 1$ implies it is right at its containment limit, while $CR > 1$ implies it has exceeded its containment limit.

Hence, $CR = 1$ takes on special significance as the boundary between likely conforming/non-conforming residual characteristics and, as such, is a suitable initial place for the decision-making threshold. However, if higher decision confidence is required or there is significant uncertainty in either the Conformance Monitoring Model or 95% confidence containment parameters, different threshold placements may be required.

Intent Inferencing

In the event of non-conformance, fault isolation techniques can then be employed to help perform intent inferencing, i.e. inferring what the aircraft *is* doing given that it *is not* following the intended conformance basis. This can be achieved by running alternate Conformance Bases or Conformance Monitoring Models (e.g. to represent different aircraft operating modes) until the residual is minimized. Even if the real behavior cannot be accurately determined, this approach enables certain behaviors to be excluded or a set of possible behaviors to be identified.

Case Study: Lateral Conformance Scenario Example

In order to investigate the utility of the proposed Conformance Monitoring Analysis Framework, the approach was used to analyze conformance monitoring under different surveillance environments for several scenarios where an aircraft was expected to be tracking a lateral trajectory.

Scenario Conformance Basis

The lateral Conformance Basis in this scenario was defined by three fixes that created a simple two-leg flight plan as shown in Figure 4. Leg track angle targets for this assumed trajectory can be calculated at the appropriate points using standard spherical-Earth navigation equations [10]. The transition at Fix 2 was assumed to be of a ‘fly-by’ type, implying a filleting of the lateral trajectory at the leg transition point.

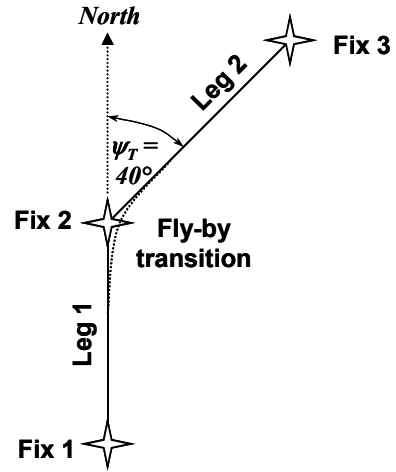


Figure 4: Scenario Lateral Conformance Basis

It was assumed that no other constraints existed other than to track the defined lateral trajectory (i.e. there were no tactical operations such as lateral offsets, holds, etc.). Speed was assumed constant at 300 kts.

A suitable version of the Surveillance State Vector for this scenario is given by Eqn. 4:

$$X_{Lateral}(t) = \left\{ \begin{array}{l} \textit{Position, } R(t) \\ \textit{Track angle, } \psi(t) \\ \textit{Roll angle, } \phi(t) \\ \textit{Track target, } \psi_T(t) \\ \textit{Planned trajectory, } T(t) \\ \textit{Destination, } D(t) \end{array} \right\} \quad \text{Eqn. 4}$$

Real World Representation

In this case study, the real world was simulated through a relatively high fidelity Simulink[®] model. The pilot intent model was limited to a simple pass-through of the relevant scenario trajectory. Aircraft intent was modeled as a block yielding the current track target by implementing the spherical Earth navigation equations on the defined trajectory. A three-loop (roll angle; track angle and cross-track error) area navigation control system model with the objective to minimize the cross-track position error [11] was used with realistic noise characteristics injected. This control system simulation was coupled to a simple point mass

dynamic model with typical commercial aircraft roll characteristics prescribed (5°/sec roll-in/roll-out, 25° maximum roll angle). The noise characteristics and gains in the control system were determined by comparing simulation output to archived data for an advanced FMS-equipped commercial aircraft.

For this case study, the surveillance systems were not explicitly modeled, so the aircraft states of position; track angle, roll angle and track target states were passed directly through to the residual generation scheme.

The resulting Simulink® real world model was programmed to fly the appropriate test scenario to generate observed states.

Conformance Monitoring Model (CMM)

A simple quantitative Conformance Monitoring Model was assumed which defined the expectations of how the position, track angle, roll angle and track target states of a point mass model would evolve along the defined lateral conformance basis if no disturbances or system noise were present. The point mass model flew directly along the legs of the defined trajectory at a constant speed until a standard rate turn of 1.5°/sec was required to be initiated to accomplish the leg transition and next track target defined in the scenario. The roll angle required to achieve this rate of heading change was calculated to give the CMM roll state.

Residual Generation & Decision-Making

Conformance Residuals were generated according to the form proposed in Eqn. 3. Observed states, x_{obs} , from the Simulink® real world representation for each test scenario were compared to those from the Conformance Monitoring Model, x_{CMM} . The Δx_{limit} parameters used as the reciprocal of each state weighting factor are given in Table 1.

Table 1: 95% Confidence State Containment Limits used in Conformance Residual

Parameter	Assumed value
RNP spec	0.5 nm
$\Delta\psi_{limit}$	5 degs
$\Delta\phi_{limit}$	10 degs
$\Delta\psi_{Tlimit}$	10 degs

An RNP 0.5 specification was assumed and the 95% confidence intervals on the other states were estimated enabling a simple decision-making threshold of $CR < 1$ representing conformance and $CR > 1$ representing non-conformance to be used.

Analysis of Test Scenarios

Three different scenarios were tested in this case study as illustrated in Figure 5:

- Scenario 1: Conforming aircraft
- Scenario 2: Non-conforming aircraft (failure to transition at Fix 2)
- Scenario 3: Ambiguous aircraft (60 second late transition at Fix 2)

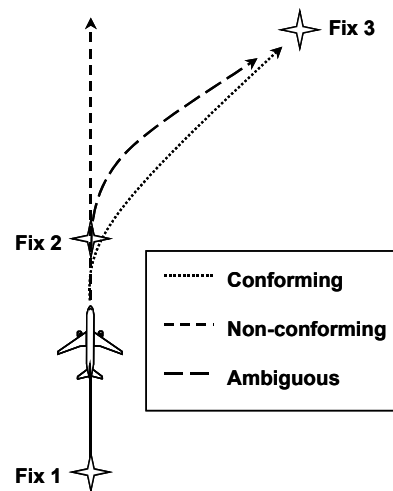


Figure 5: Case Study Test Scenarios

Scenarios 1 & 2: Conforming & Non-conforming Behaviors

Figure 6 illustrates the ground tracks, track angle, roll angle and track target states respectively for the Conformance Monitoring Model (CMM) and the observed states from the scenarios of conforming and non-conforming aircraft. The right side of the figure also details the individual residual on each state (i.e. the difference between the state value observed in the scenario from the Simulink® real world model and the expected state value from the CMM, $|x_{obs} - x_{CMM}|$). Conformance Residuals were calculated using different state combinations (position only; position & track angle; position, track angle & roll angle; position & track target) and are presented in Figure 7.

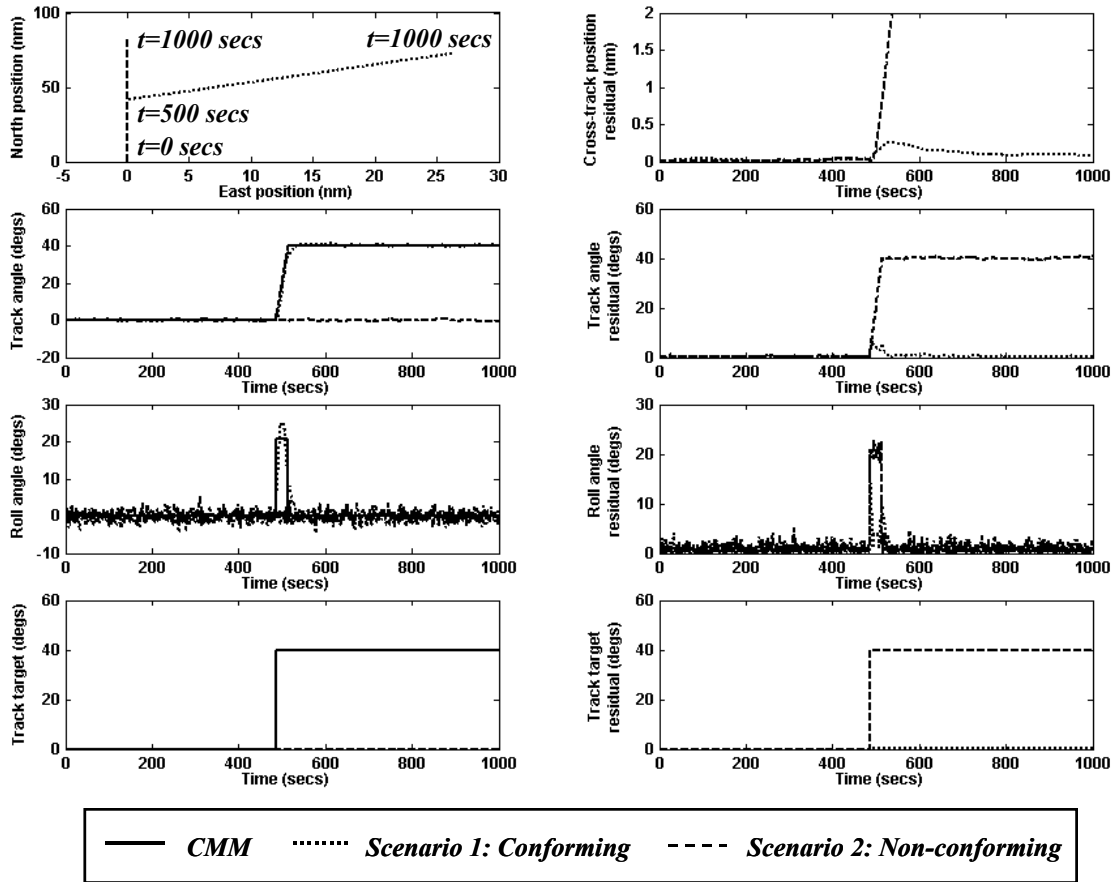


Figure 6: Scenarios 1 & 2 State Behaviors (left) & State Residuals (right)

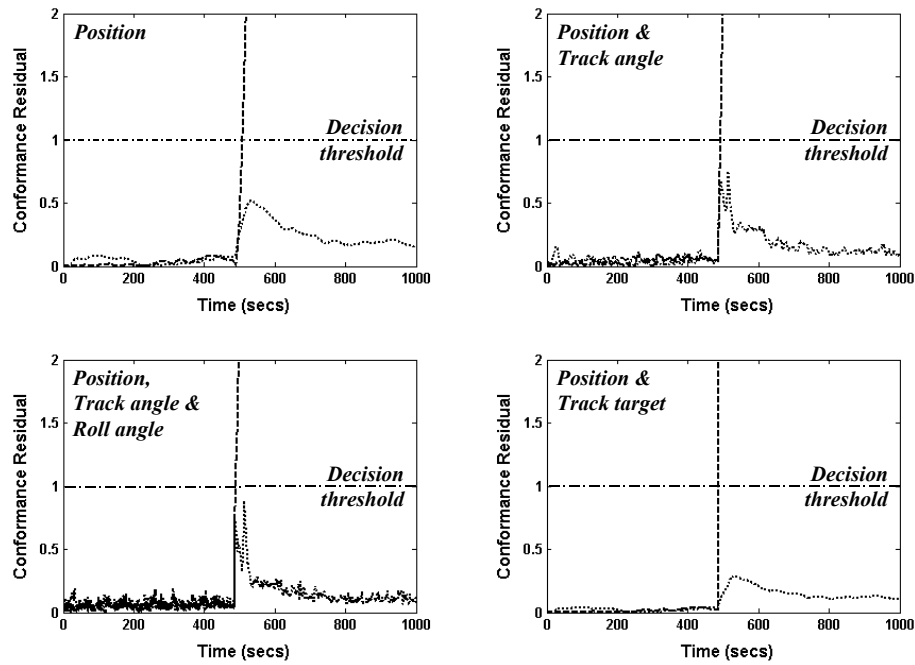


Figure 7: Scenarios 1 & 2 Conformance Residuals Using Different State Combinations

Assuming that non-conformance is declared when the Conformance Residual exceeds unity, some interesting insights can be gained from the analysis. The different behaviors of the Conformance Residuals for the two scenarios can be clearly seen in Figure 7: the Conformance Residual for the conforming case remains below unity while that for non-conforming case increases rapidly above unity when the expected turn is not made. Detailed examination of the Conformance Residual plots reveals that the inclusion of relevant higher order states enables faster detection of non-conforming behavior compared to when position alone is used. In this scenario, the CMM predicted the leg transition to start at 485 secs: with position only, the non-conformance was detected ($CR > 1$) at 23 sec after the predicted start of transition; with position & track angle it was detected after 8 sec; with position, track angle & roll angle it was detected at 4 sec and with position & track target it was detected within 1 sec.

In this example, the inclusion of the higher order states was providing more evidence regarding the behavior of the aircraft in the Conformance Residual. However, the results imply several corollaries which impact how Conformance Residuals should be generated and analyzed. Assuming that speed of detection of non-conformance is an effective performance metric, the Conformance Residual only performs better when it is provided with *relevant* states. While the inclusion of higher order dynamic states improves the time-to-detection performance of the Conformance Residuals, they add increasing amounts of noise (easily observable in the position, track angle & roll angle Conformance Residual of Figure 7) which increases the potential for false alarms. As such, care is required in the selection of the states to be included in the Conformance Residual to ensure BOTH good time-to-detection and insensitivity to false alarms.

Analysis of the benefits of access to the track target state raises additional questions. Although in this example the non-conformance could be detected within 1 sec when this state was included in the Conformance Residual and without the noise associated with high order dynamic states, it is most

effective when the time of transition initiation is well-known. This may not be the case in general since unknown pilot- and/or FMS logic-induced lags may be present. The Conformance Monitoring Analysis Framework enables these issues to be studied and future work will begin to address them.

Scenario 3: Ambiguous Behavior

Figure 8 illustrates the ground tracks, track angle, roll angle and track target states for the CMM and the observed behaviors for Scenario 3: an aircraft turning late at Fix 2. As before, the right hand side of the figure details the residuals for each state. Conformance Residuals were calculated using the same state combinations as before and are presented in Figure 9. In this case, the Conformance Residuals increase when the transition fails to occur at the expected time and then gradually reduce as the turn is made.

These results provide further evidence for the findings discussed for Scenarios 1 & 2 in terms of the benefits and disadvantages of various state combinations. The importance of timing is highlighted again here in the behavior of the higher order residuals of Figure 8. The double spike in the roll angle residual, for example, is caused by the failure to make the turn at the expected time (first spike) and then making the turn late when the CMM is not predicting one (second spike). Future work will investigate when it is appropriate to give 'credit' in the Conformance Residual for correct (but late or early) behaviors using correlation techniques to correct out timing ambiguity.

Although the analysis performed here is based on relatively simple models, it is clear that this approach could provide a basis for investigating the impact of different state environments on the conformance monitoring task, for example to determine which states should be included in future datalink messages [e.g. 12]. Such a study would be required to consider the results in context of how accessible and useful each of the required states would be. For example, although the current target state information may provide significant benefit to the conformance monitoring task, such states may be difficult or expensive to surveil.

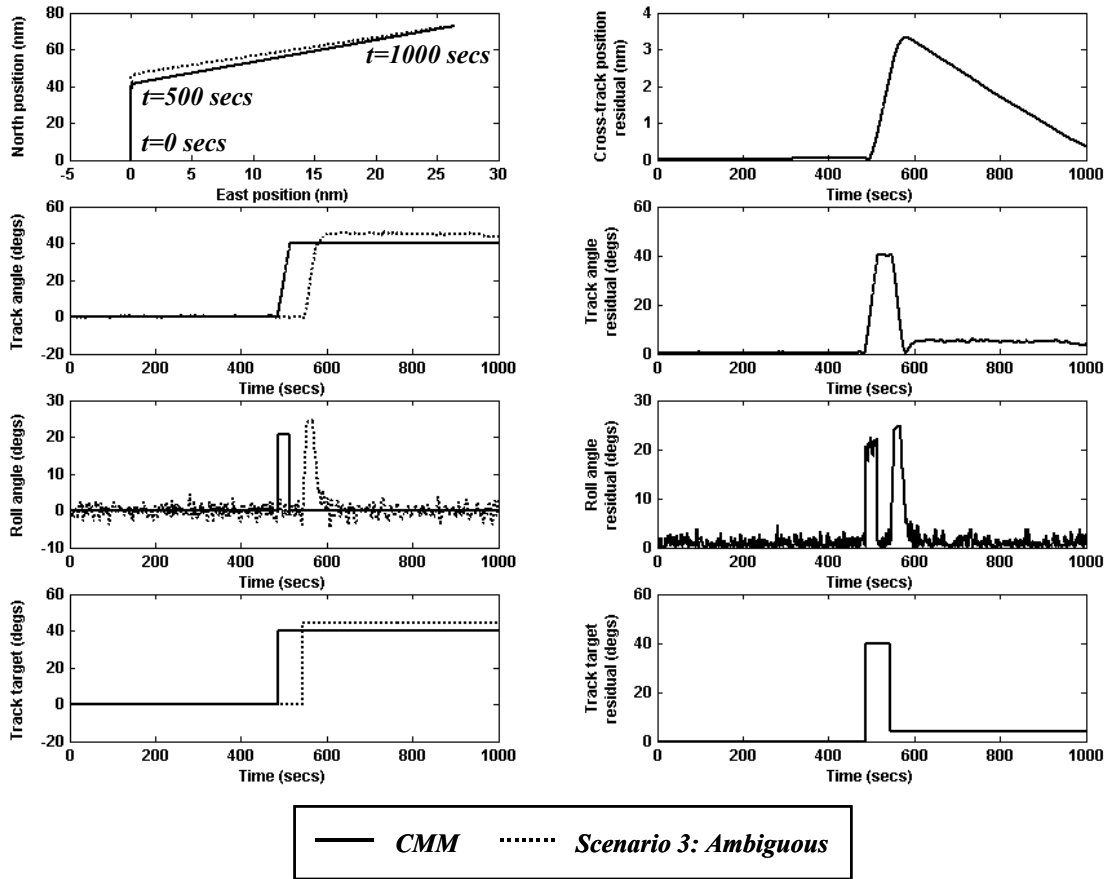


Figure 8: Scenario 3 State Behaviors (left) & State Residuals (right)

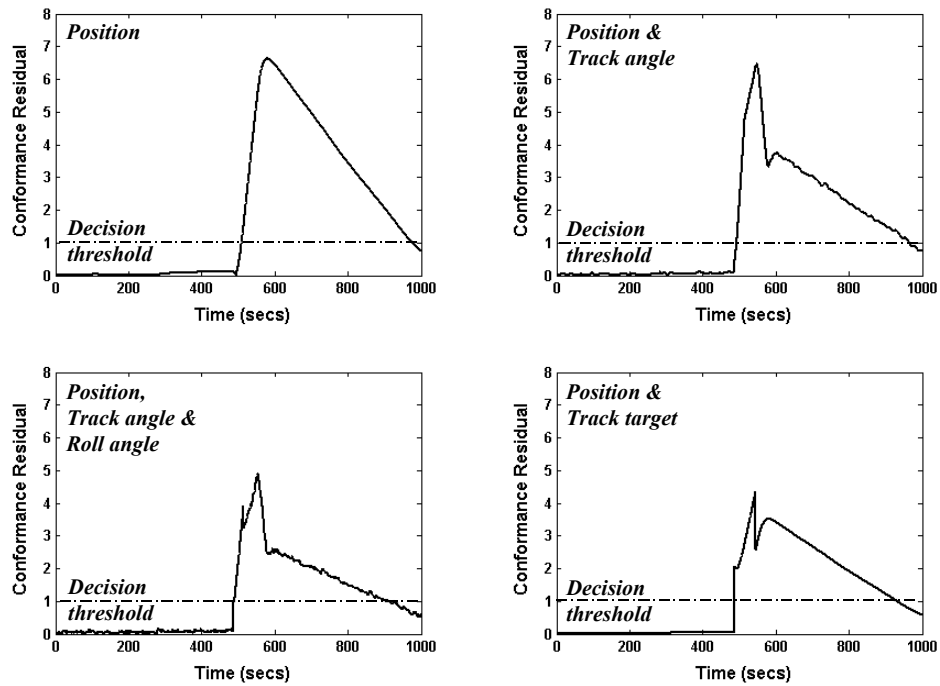


Figure 9: Scenario 3 Conformance Residuals Using Different State Combinations

Intent Inferencing

As an illustration of the proposed approach to intent inferencing, a number of alternative intents are postulated for the case of the late-turning aircraft of case study Scenario 3 discussed above. In order to bound the problem, a subset of trajectories associated with likely alternate behaviors from that expected can be proposed. In general, proposals could be based on sensible assumptions, such as:

- ‘no change’ (i.e. dead-reckoning)
- ‘historical errors’ (e.g. errors seen in historical data for the baseline trajectory, such as having waypoints with similar names in close proximity)
- ‘critical errors’ (e.g. errors that could have immediate hazardous consequences, such as unauthorized flights into very busy or sensitive areas)
- ‘direct-to’ (i.e. by-passing the next fix)

The proposed alternate hypotheses are shown in Figure 10, along with the actual Scenario 3 trajectory flown by the Simulink® real world model. The ‘baseline’ trajectory represents the expected Conformance Basis for the aircraft.

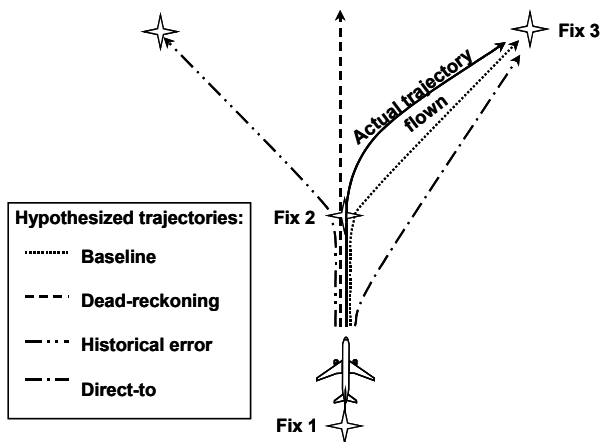


Figure 10: Hypothesized Alternate Trajectories

These alternate trajectories can be tested in parallel with the baseline trajectory by running a separate CMM for each of the hypothesized trajectories to be tested. The resulting Conformance

Residual for each of these trajectories gives an indication of the relative likelihood that the aircraft is following that trajectory. In general, the most likely hypotheses are those with the smaller Conformance Residuals. The Conformance Residual corresponding to each of the proposed hypothesized trajectories can be determined using the available states—Figure 11 assumes position and track angle states are available.

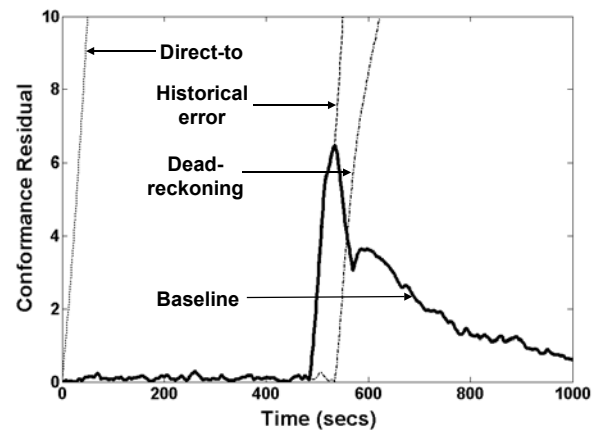


Figure 11: Conformance Residuals for Hypothesized Alternate Trajectories

It is useful to determine some criteria to discard hypotheses that are clearly not supported by the observed evidence. In this example, a hypothesis discard threshold of $CR = 10$ was used. The ‘direct-to’ hypothesis (that directly connecting the initial aircraft position to Fix 3) can be quickly eliminated as its Conformance Residual increases rapidly, while the other three alternates are initially similar and thus still viable hypotheses. When the aircraft does not make the turn at the expected position (either way), the ‘baseline’ and ‘historical error’ trajectory Conformance Residuals increase relative to the ‘dead-reckoning’. At this point, the highest likelihood is associated with the aircraft following close to the ‘dead-reckoning’ trajectory. However, when the turn towards Fix 3 is finally initiated, the ‘baseline’ trajectory Conformance Residual decreases while the ‘dead-reckoning’ and ‘historical error’ trajectory Conformance Residuals increase, indicating a relative shift in the likelihood that the trajectory being followed is back towards the ‘baseline’. Finally, all trajectories other than those close to the ‘baseline’ become highly

unlikely. If none of the proposed trajectories result in a small enough Conformance Residual, the search space of feasible trajectories may need to be enlarged or other means of inferring intent initiated.

Conclusions & Future Work

Conformance monitoring is of fundamental importance to ATC operations and future surveillance environments may enable more sophisticated procedures to be developed for this task. A Conformance Monitoring Analysis Framework has been presented which enables model-based fault detection and isolation techniques to be employed to investigate many important issues. The essential concepts of Conformance Residual generation; decision-making and intent inferencing have been identified and a lateral trajectory case study using a very simple Conformance Monitoring Model has been used to illustrate the promise of this approach for investigating different state environments. Preliminary results indicate potential improved time-to-detection performance associated with using relevant higher order states in addition to position, but this is at the expense of greater noise in the Conformance Residual. Use of intent states such as current target states hold promise for rapid detection of non-conformance, but introduce other challenges associated with timing differences between the real world and the Conformance Monitoring Model.

Future work will expand on the framework introduced here. Implementation issues such as using commercial flight simulators for the real world representation, testing higher fidelity Conformance Monitoring Models, determining the 95% state containment limits (e.g. using prior observations) and appropriate threshold placement for various types of operations will be explored. Application to other domains such as vertical and temporal will also be considered with the ultimate objective of investigating datalink state requirements for future ATC operations.

Acknowledgements

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