An Adaptive Time Series Framework for Aircraft 4D Trajectory Conformance Monitoring

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***Abstract*— The general problem of conformance monitoring with respect to preassigned 4-dimensional (4D) trajectories equipped with corresponding 4D margins (4D contracts) is considered within an adaptive statistical time series framework. The specific issues tackled within this context are: (a) Present conformance monitoring and quality of conformance evaluation via statistical tools, which also leads to abnormal event detection; (b) future conformance monitoring, in which the conformance is predicted ahead of time, allowing for potentially corrective or other actions. The performance of the developed methods is assessed via simulations. In present conformance monitoring, an alarm is shown to be issued instantaneously, following the emergence of an abnormal event. In future conformance monitoring, the comparison with a scheme based on nominal probabilistic trajectory prediction demonstrates the benefits of the adaptive statistical time series framework.**

I. Introduction

The primary goal of navigation monitoring is to ensure the safety, security and efficiency of air traffic operations [1], [2]. In order to achieve these aims, flight plans are issued for each aircraft, and clearances are created and issued by air traffic controllers given the constraints of the Air Traffic Control (ATC) system design. In future ATC concepts, these clearances may be based on aircraft-preferred conflict-free trajectories that are authorized by a centralized ground unit. In any case, an ATC function is required to ensure that the aircraft adhere to their assigned clearances by detecting excessive deviations that could compromise system operation, enabling corrective action to be initiated when required. This function is referred to as conformance monitoring [1]–[3].

General conformance monitoring has, in its current sense, been typically performed by ATC, by comparing radar data with assigned flight paths [1]. Significant delays often exist before an aircraft non-conformance may be detected; this is due to surveillance and workload limitations, as well as the requirement to account for numerous, distinct, aircraft tracking capabilities. The issue of present conformance monitoring has been addressed in a number of studies [1]–[4]. Nevertheless, limited attention has been paid to the task of future (predictive) conformance monitoring [5]. Although several trajectory prediction methodologies – which play a core role in this context – have been suggested [6], [7], very few studies treat the issue of future conformance monitoring [5]. Trajectory prediction methodologies may be generally divided into three categories: nominal, worst case, and probabilistic [6]. Nominal methods predict the aircraft position by propagating the aircraft states into the future without taking into account uncertainties. Worst-case methods assume that the aircraft will perform any of a set of prescribed maneuvers and the worst case one is selected for trajectory prediction. Probabilistic methods predict the future trajectory by taking into account uncertainties. For a review of the various methods the reader is referred to [6].

The 4D trajectory concept, that is being at a pre-assigned specific position at a given time, has been recently reformulated into the form of *4D contracts* in [8]–[10]. First, the ground segment of the system is in charge of generating conflict-free 4D trajectories with corresponding contract margins (the 4D contracts) according to demand and airspace capacity. Then, the aircraft are assigned the generated 4D contracts and have the responsibility to comply with them. Hence, conformance of each actually flown 4D trajectory with respect to its assigned counterpart, needs to be continuously monitored. For details the reader is referred to [8]–[10] and references therein.

The focus of the present study is on the problem of conformance monitoring with respect to preassigned 4D contracts. Two specific issues are considered and corresponding methods are developed within an *adaptive statistical time series framework*: (a) *Present conformance monitoring* (simply referred to as conformance monitoring) and *quality of conformance* evaluation via statistical tools, which also leads to the early detection of events that may potentially lead to either lack of conformance or degraded quality of conformance. (b) *Future conformance monitoring*, in which the conformance is predicted ahead of time, potentially allowing for the initiation of proper actions before unacceptable deviations from the planned trajectory and its assigned margins actually occur. The performance of the developed methods is assessed via simulation. The attained future conformance is compared with that of a scheme based on nominal probabilistic trajectory prediction [11], [12].

An advantage of the adaptive time series framework lies with the fact that there may be no absolute need (although improvements would be possible) for taking the aircraft intent into account, nor for analytical expressions of the aircraft kinematic equations, which necessitate the use of elaborate techniques and time consuming algorithms for prediction [3], [7]. On the contrary, it is based on relatively simple time-varying adaptive time series models that are

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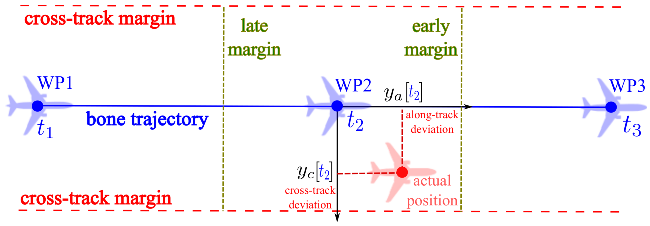

Fig. 1. Schematic representation of the contract bone trajectory and the contract margins in the local navigation frame (no altitude shown); instantaneous (time instant t_2) along-track and cross-track sample deviations are also depicted.

capable of modeling the along-track, cross-track, and altitude deviations with respect to a preassigned contract.

The paper is organized as follows: Present conformance monitoring is discussed in Section II. Future conformance monitoring is presented in Section III, while simulation results are presented in Section IV. Concluding remarks are summarized in Section V.

II. Present Conformance Monitoring

A. Preamble

A main element of a 4D contract is the *bone trajectory*, which is the nominal trajectory and the element of the contract that should be as close as possible to the actually flown 4D trajectory. The bone trajectory is formed by successive 4D waypoints (WPs), which define its geometry. The *Contract Bubble (CB)* is formed around the bone trajectory, by defining contract margins in all directions as pairs (i.e. early/late for along-track, left/right for cross-track, and low/high for altitude). An aircraft complies with its contract as long as it stays within a restricted part of its CB, which is referred to as the Freedom Bubble (FB) and is produced by eroding the CB by safety margins that ensure minimum separation [this is done by defining a Safety Bubble (SB) around the aircraft position]. See [8]–[10] and references therein for details.

In the context of the present article, and for simplicity of presentation, explicit reference is made only to the bone trajectory and the CB. The latter is considered violated as soon as its margins are, in any direction, exceeded.

A schematic representation of the contract bone trajectory (in the local navigation frame – no altitude is shown) and the corresponding along-track and cross-track contract margins are presented in Fig. 1, along with an example of instantaneous along-track and cross-track flown trajectory deviations.

B. Conformance monitoring

In general, the aircraft position state vector is defined as[1]:

$$\boldsymbol{x}[t] = \left[x_1[t]\ x_2[t]\ x_3[t]\right]^T \tag{1}$$

with $x_1[t]$ and $x_2[t]$ designating the coordinates in the local navigation frame (the x_1 axis pointing at the aircraft heading direction), and $x_3[t]$ the altitude coordinate.

In the context of conformance monitoring, the aircraft trajectory deviations from the contract bone trajectory are referred to as the *Conformance Residuals (CRs)* [1], [2]. These represent the difference between the actual (observed) aircraft 3D position, available through surveillance, and the expected aircraft position as described by its assigned contract bone trajectory at any time instant t (see Fig. 1). Present conformance monitoring is then achieved via the on-line monitoring of the CRs and their comparison to the allowable margins.

C. Statistical quality of conformance monitoring

The problems of on-line monitoring of the quality of conformance and the early detection of abnormal (or hazardous) events is treated via proper statistical tools. When an aircraft experiences abnormal conditions, such as severe turbulence, winds, or other hazardous events such as system failure, the mean and/or variance of the trajectory deviations are expected to change, leading to a decrease in conformance quality. $\bar{x}$ and S control charts [13] may be employed to monitor the quality of conformance and also detect changes which may be due to various events.

As the statistical tools referring to quality assurance require serially uncorrelated observations [13] – which is for obvious reasons violated by the aircraft contract deviation signals – proper pre-processing is necessary. The measured contract deviation signals are thus modeled within a non-stationary adaptive time series modeling framework using Recursive AutoRegressive (RAR) models – for details the reader is referred to section (III-B). This type of modeling is necessary in order to properly account for serial correlation and also for the non-stationarity present in each signal. Following this, statistical quality assurance tools are applied on the residual (one-step-head prediction error) signal which fulfills the serial uncorrelatedness assumption.

Using the contract deviation residual signal $e[t+1|t]$, its standard deviation $\sigma_e[t]$ is estimated via a sliding window of length m. Then the sample standard deviation[2] $\widehat{\sigma}_e[t]$ becomes the charted value using an S control chart [13, p. 230]. The average value of the standard deviation is designated as $\bar{S}$. The upper control limit (UCL), control limit (CL) and the lower control limit (LCL) are defined as $UCL = B_4\bar{S}$, $CL = \bar{S}$ and $LCL = B_3\bar{S}$, respectively. The values of B_3, B_4 are obtained based on the window length m by the following relations, or else directly from statistical tables [13]:

$$B_3 = 1 - \frac{3}{c_4\sqrt{2(m-1)}}, \quad B_4 = 1 + \frac{3}{c_4\sqrt{2(m-1)}} \tag{2}$$

$$\text{with} \quad c_4 = \frac{4(m-1)}{4m-3}. \tag{3}$$

[1] Bold face upper/lower case symbols designate matrix/column-vector quantities, respectively.

[2] A hat designates estimator/estimate of the indicated quantity.

The S chart, with its limits, thus constitutes a statistical measure of the conformance quality which may be continuously monitored. Abnormal deviations, beyond the established limits, function as alarms for changes (for instance degradation) in quality, and are, expectedly, associated with various root events. It has been shown that the control limits based on the normality assumption can often be successfully used unless the population is extremely non-normal [13, p. 203].

III. Future conformance monitoring

Future conformance monitoring is treated via the use of two distinct trajectory prediction methods: A nominal probabilistic method and an adaptive time series based method.

A. Method A: The nominal probabilistic prediction method

In [11], [14] a simple probabilistic description of the global effects of the perturbations affecting the aircraft motion is described. The predicted aircraft position is calculated by propagating the present aircraft states into the future along a single trajectory. The predicted deviations are represented by zero-mean Gaussian random variables.

The variance of the along-track component $\sigma_a^2(t)$ is considered growing quadratically with time t, while the variance of the cross-track component $\sigma_c^2(t)$ is growing quadratically with the travelled distance $s(t)$, until it saturates to a fixed value $\bar{\sigma}_c^2$. The along-track and cross-track components are assumed to be *mutually independent*. The variance of the vertical component is considered to remain constant [11], [14]. Hence:

$$\sigma_a^2(t) = r_a^2 \cdot t, \quad \sigma_c^2(t) = \min\{r_c^2 \cdot s^2(t), \bar{\sigma}_c^2\}. \tag{4}$$

The subscripts a, c refer to the along-track and cross-track directions, respectively. In [11], it is argued that this model is fairly accurate for predicting the position of an aircraft over a mid-term horizon in the order of 20 min.

Presently the case of level flight is considered. This is done primarily for ease of presentation, while the generalization to the 3D case is straightforward. It is assumed that the aircraft receives a 4D contract from the ATC in terms of a sequence of $n+1$ waypoints $\{WP_j\}_{j=0,\ldots,n}$, $WP_j \in \mathbb{R}^2$, that are to be reached at specific times.

Following [14], it is assumed that the predicted (at time t for the future time $t+h$; hence prediction horizon h) aircraft position $\widehat{\boldsymbol{x}}[t+h|t]$ may be modeled as a Gaussian random vector:

$$\widehat{\boldsymbol{x}}[t+h|t] = [\widehat{x}_1[t+h|t] \;\; \widehat{x}_2[t+h|t]] \in \mathbb{R}^2 \tag{5}$$

$$\widehat{\boldsymbol{x}}[t+h|t] \sim \mathcal{N}(\boldsymbol{x}[t+h], \boldsymbol{\Sigma}(h)). \tag{6}$$

with mean $\boldsymbol{x}[t+h]$ coinciding with the *actual future position* of the aircraft and covariance matrix $\boldsymbol{\Sigma}(h)$. The expression $\mathcal{N}(\cdot,\cdot)$ designates Gaussian distribution with the indicated mean and covariance.

Let θ_j designate the heading of the aircraft at time $t+h \in [T_{j-1}, T_j)$, with T_j denoting the arrival time at the way point WP_j. Then, the covariance matrix $\boldsymbol{\Sigma}(h)$ is given by:

$$\boldsymbol{\Sigma}(h) = \boldsymbol{R}(\theta_j)\bar{\boldsymbol{\Sigma}}(h)\boldsymbol{R}(\theta_j)^T, \; \bar{\boldsymbol{\Sigma}}(h) = diag(\sigma_a^2(h), \sigma_c^2(h)) \tag{7}$$

with $\bar{\boldsymbol{\Sigma}}(h)$ designating the covariance matrix in the body coordinate frame. $\boldsymbol{R}(\theta)$ is the rotation matrix associated with the aircraft heading θ_j [11], [14].

B. Method B: The adaptive time series prediction method

As already mentioned, the time-varying nature of the contract deviation signal characteristics – due to the continuously changing environmental (wind, gusts) and flying conditions – necessitates the use of appropriate adaptive model structures with parameters that continuously adapt to the changing dynamics. An adaptive scheme that is based on Recursive AutoRegressive (RAR) modeling of the contract deviations is thus introduced. The RAR(na) model, with na designating the AutoRegressive (AR) order, is of the form:

$$A(\mathcal{B},t) \cdot y[t] = e[t], \quad e[t] \sim \mathcal{N}(0, \sigma_e^2[t]) \tag{8}$$

$$A(\mathcal{B},t) = 1 + a_1[t]\cdot\mathcal{B} + a_2[t]\cdot\mathcal{B}^2 + \ldots + a_{na}[t]\cdot\mathcal{B}^{na} \tag{9}$$

with t referring to normalized discrete time (with the corresponding actual time being $(t-1)T_s$, with T_s designating the sampling period), $y[t]$ the along-track or cross-track contract deviation signal, and $e[t]$ an (unobservable) uncorrelated (white) *innovations* sequence with zero mean and variance $\sigma_e^2[t]$. $\mathcal{B}$ designates the backshift operator ($\mathcal{B}^i \cdot y[t] = y[t-i]$), and $a_i[t]$ the i-th AR parameter at time t.

The estimation of the model parameter vector $\boldsymbol{\theta}[t] = [a_1[t] \;\ldots\; a_{na}[t]]^T$ is based on minimization of the *weighted least squares (WLS) criterion* [15, pp. 363–368]:

$$\widehat{\boldsymbol{\theta}}[t] = \arg\min_{\boldsymbol{\theta}[t]} \sum_{\tau=1}^{t} \lambda^{t-\tau} \cdot e^2[\tau, \boldsymbol{\theta}^{\tau-1}] \tag{10}$$

with:

$$e[t, \boldsymbol{\theta}^{t-1}] = A(\mathcal{B},t)\cdot y[t] = y[t] + \sum_{i=1}^{na} a_i[t]\cdot y[t-i] \tag{11}$$

designating the model's one-step-ahead prediction error (residual) $e[t|t-1]$; the prediction is computed using the model parameters at time instant $t-1$ as those corresponding to t are not available at time $t-1$. The term $\lambda^{t-\tau}$ is a weighting function that, for $\lambda \in (0,1)$, assigns more weight to more recent deviations. λ is referred to as the *forgetting factor*.

The smaller the value of λ, the faster older values of the error (and thus the signal) are forgotten, thus increasing the estimator adaptability (its ability to track the evolution of the dynamics). Yet, at the same time, the accuracy of the estimator decreases, as its covariance increases [15, pp. 381–382]. Therefore, the selection of λ is crucial as it represents the basic trade-off between tracking ability and achievable parameter accuracy. The minimization of (10) leads to the well-known Recursive Least Squares (RLS) algorithm (Matlab function *rarx.m*) [15, pp. 363–369].

The innovations (residual) variance $\sigma_e^2[t]$ may be estimated via a window of length m that slides over the prediction error (residuals) sequence, that is:

$$\widehat{\sigma}_e^2[t] = \frac{1}{m}\sum_{t-m+1}^{t} \widehat{e}^2[t|t-1]. \tag{12}$$

At each time instant the corresponding estimated RAR(na) model parameter vector $\widehat{\boldsymbol{\theta}}[t]$ is employed for the computation of the h-step-ahead prediction $\widehat{y}[t+h|t]$ of the contract deviations signal, with $\widehat{y}[t+h|t] \sim \mathcal{N}(y[t+h], \sigma_y^2[t+h|t])$ [16, pp. 131–135]. For details on the computation of $\widehat{y}[t+h|t]$ the reader is referred to [15, pp. 70–72]. Once the predicted value of the signal $\widehat{y}[t+h|t]$ is available, the prediction error variance is estimated as:

$$\sigma_y^2[t+h|t] = Var\big[e[t+h|t]\big] = \sum_{j=1}^{h-1} G_j^2[t] \cdot \sigma_e^2[t] \qquad (13)$$

where $e[t+h|t] \equiv e[t+h]$ is the prediction error sequence and $\sigma_e^2[t]$ its time-varying variance estimated as in (12). $G_j[t]$ designates the j-th Green's function coefficient. It is important to mention that due to the time-varying model parameters, the Green's function coefficients are calculated considering that the backshift operator obeys a non-commutative ("skew") multiplication algebra ("$\circ$"), defined such that $\mathcal{B}^i \circ \mathcal{B}^j = \mathcal{B}^{i+j}$, $\mathcal{B}^i \circ y[t] = y[t-i] \cdot \mathcal{B}^i$. For details the reader is referred to [17] and references therein. The interval predictions of $y[t+h]$ made at time t are then (at the $1-\alpha$ confidence level):

$$\widehat{y}[t+h|t] \pm Z_{1-\frac{\alpha}{2}} \cdot \widehat{\sigma}_y[t+h|t] \qquad (14)$$

with $Z_{1-\frac{\alpha}{2}}$ designating the normal distribution's $1-\frac{\alpha}{2}$ critical point.

C. Checking future conformance

Standing at time t, future (for time $t+h$) conformance monitoring, taking uncertainties into account, is based on statistical confirmation that the along-track and cross-track contract future (at time $t+h$) deviations shall be smaller, in magnitude, than the corresponding contract margins $\delta_i[t+h]$ (>0). This is accomplished by setting up a formal statistical hypothesis testing problem of the form:

$$\begin{array}{lll} H_o: & |y_i[t+h]| \leq \delta_i[t+h] & \text{(conformance)} \\ H_1: & \text{otherwise} & \text{(non-conformance)} \end{array} \qquad (15)$$

with $i=a,c$ for the along-track and cross-track deviations, respectively. As the contract deviations $y_i[t+h]$ are of course not available at the present time t, their corresponding h-step-ahead predicted values $\widehat{y}_i[t+h|t]$ are employed, with $\widehat{y}_i[t+h|t] \sim \mathcal{N}(y_i[t+h], \sigma_{y_i}^2[t+h|t])$ [16, pp. 131–135]. The variance $\sigma_{y_i}^2[t+h|t]$ is generally unknown, but may be also estimated via (13) using estimates of the involved quantities. Assuming negligible variability of the estimated variance $\widehat{\sigma}_{y_i}^2[t+h|t]$, leads to the following decision making (conservative decision with maximum Type I error probability, that is probability of accepting the non-conformance hypothesis when the conformance hypothesis is actually true, equal to α):

$$\begin{array}{rll} Z_A < Z_{1-\alpha} \text{ (when } \widehat{y}_i[t+h|t] > 0) & \Rightarrow & H_o \text{ is accepted} \\ Z_B > Z_{\alpha} \text{ (when } \widehat{y}_i[t+h|t] < 0) & \Rightarrow & H_o \text{ is accepted} \\ \text{Else} & \Rightarrow & H_1 \text{ is accepted} \end{array} \qquad (16)$$

with $Z_{1-\alpha}, Z_\alpha$ designating the standard normal distribution's $1-\alpha, \alpha$ critical points, respectively. Z_A and Z_B are defined as:

$$Z_A = \frac{\widehat{y}_i[t+h|t] - \delta_i[t+h]}{\widehat{\sigma}_{y_i}[t+h|t]}, Z_B = \frac{\widehat{y}_i[t+h|t] + \delta_i[t+h]}{\widehat{\sigma}_{y_i}[t+h|t]} \qquad (17)$$

An alternative approach, perhaps more intuitive and appropriate for informing the aircrew and ATC, would be to estimate the future probability of non-conformance $P(NC)$.

TABLE I
DETAILS ON THE SIMULATED 4D CONTRACT

Number of WPs	11
WP altitude	FL300
WP interval distance	87.3 s (11 nmi)
Initial a/c heading	36.5^o
Along-track margin	$\delta_a = \pm 25$ s (early/late margins)
Cross-track margin	$\delta_c = \pm 1.49$ nmi

TABLE II
SIMULATED FLIGHT DETAILS

Aircraft type	Boeing 737–500 (JSBSim simulator)
Flight duration	868 s
Cruise speed	0.74 mach
Turbulence	moderate
Heading deviation	$+3.5^o$ at $t_d = 436$ s
Contract violation time	$t_v = 650$ s (cross-track violation)

IV. Simulation results

A simulation scenario is conducted using the open source JSBSim flight simulator [18]. The scenario involves a Boeing 737 aircraft during cruise flight which initially complies with its contract. Then a heading deviation of 3.5^o is introduced at $t_d = 436$ s. This later results in non-conformance, as the cross-track margin $\delta_c = 1.49$ nmi is exceeded at time $t_v = 650$ s. The contract and simulation details are presented in Tables I and II, respectively.

A. Adaptive time series modeling

For the selection of the AR order na and the forgetting factor λ, the RSS/SSS (Residuals Sum of Squares/Signal Sum of Squares) criterion, describing the predictive ability of the model, is employed in an off-line procedure using historical flight data. AR orders up to 20 and forgetting factor values $\lambda \in [0.93, 0.999]$ (incremental step of 0.001) are considered. Table III presents the selected adaptive model forms (for both the along-track and cross-track deviations) and estimation details.

B. Present conformance monitoring

The S-chart based statistical quality control scheme employs an adaptive RAR(18) model for capturing the contract deviation dynamics (see Table III). Fig. 2 demonstrates the ability of the method to indicate that the quality of conformance has been degraded once the heading deviation is introduced at time t_d (vertical dashed line). The horizontal dashed line indicates the upper control limit. Conformance

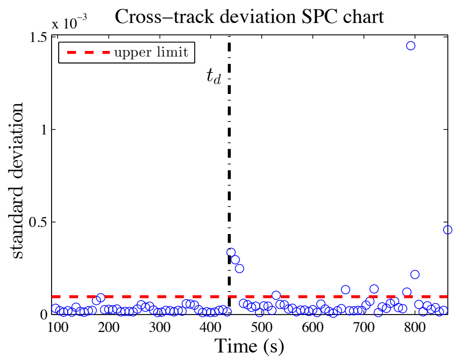

Fig. 2. Statistical quality of conformance monitoring and event detection via the S-chart. The horizontal dashed line designates the upper control limit. The heading deviation is introduced at t_d = 436 s (dashed vertical line).

TABLE III
ADAPTIVE MODEL ESTIMATION DETAILS

Sampling period	$T_s = 1$ s (quality of conformance) $T_s = 5$ s (future conformance)
Along-track adaptive model	RAR(18), $\lambda = 0.970$
Cross-track adaptive model	RAR(18), $\lambda = 0.958$
Residual variance estimation	Moving window length $m = 8$

RLS estimation method [15, pp. 363–369].

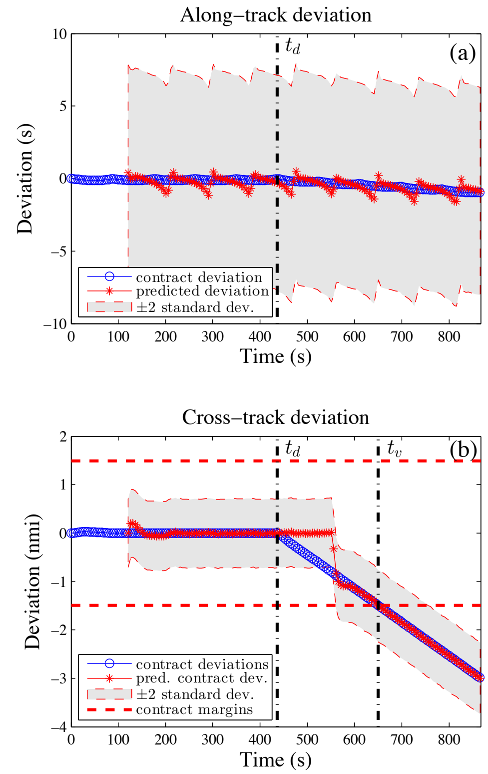

Fig. 3. Nominal probabilistic method based contract deviation predictions (prediction horizon of 120 s): actual versus predicted contract deviations along with the corresponding ±2 standard deviation confidence intervals (shaded areas). (a) Along-track deviation in seconds and (b) cross-track deviation in nautical miles. The vertical dashed lines indicate the time instants t_d and t_v at which the heading deviation is introduced and the contract is violated, respectively. The horizontal dashed line designates the cross-track (lateral) contract margins.

quality, as monitored by the $\bar{S}$ chart, almost instantly exceeds the upper control limit as soon as the heading deviation is introduced. This demonstrates that the method is capable of providing an *immediate* alert for degraded quality of conformance and detrimental event occurrence.

C. Future conformance monitoring

The predicted along-track and cross-track deviations, along with the corresponding ± 2 standard deviation confidence intervals as obtained by the nominal probabilistic method for a prediction horizon of 120 seconds, are depicted in Fig. 3. The vertical dashed lines indicate the time instants t_d and t_v at which the heading deviation is introduced and the contract is violated, respectively. The horizontal dashed line designates the cross-track contract margin. It is evident that the margin is exceeded at $t = 650$ s. Notice that the along-track deviation remains less than 1 s throughout the cruise duration, and that the deviation confidence intervals remain constant during the flight as they depend only on the employed prediction horizon.

Furthermore, Fig. 4 presents the adaptive time series (RAR(18) model) based predicted contract deviations for a prediction horizon of 120 seconds, while Fig. 5 demonstrates the ability of the adaptive model to provide narrower confidence intervals for the predicted contract deviations (compare with Fig. 3). By comparing the resulting contract deviation prediction errors obtained by both methods (Figs. 3–5), it is evident that the along-track deviation prediction errors obtained by the adaptive RAR model based method are significantly smaller than their nominal probabilistic counterparts. On the other hand, with respect to the cross-track deviation prediction error, both methods perform equally well, as the obtained prediction errors are similar, with only a slight prevalence of the adaptive model based method.

The probability of non-conformance for a prediction horizon of 120 seconds is, for both methods, depicted in Fig. 6 as a function of time. For the actual contract violation time $t_v =$ 650 s, the nominal probabilistic method yields a predicted probability of cross-track non-conformance $P(NC) = 0.51$, while the adaptive time series based method yields a respective probability $P(NC) = 0.55$. Moreover, the nominal probabilistic method achieves a cross-track non-conformance probability $P(NC) = 0.95$ at flight time $t_{0.95} = 736$ s. This probability is achieved by the adaptive time series based method at time $t_{0.95} = 719$ s, which is 27 seconds *earlier* than the nominal probabilistic method.

Finally, the CPU time for predicting 120 s ahead of time is 0.0017 s for the nominal probabilistic method and 0.0055 s for the adaptive time series method. Thus, the former (nominal probabilistic method) requires CPU time equal to 30.9% of that of the letter (adaptive time series method). Nevertheless, it is evident that both methods may be effectively applied on-line.

V. CONCLUDING REMARKS

The problems of present and future conformance monitoring have been addressed via methods developed within

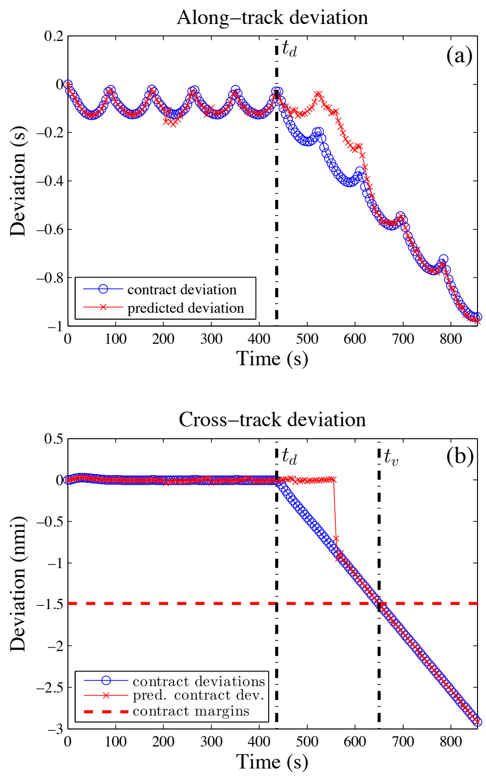

Fig. 4. Adaptive RAR model method: Predicted (prediction horizon of 120 s) versus actual contract deviations. (a) Along–track; (b) cross–track (in this case contract margins are depicted as dashed red lines.)

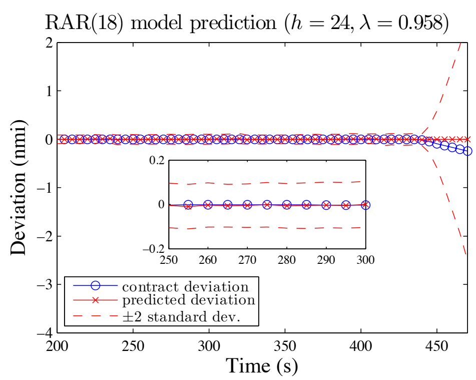

Fig. 5. Adaptive RAR model method: Predicted (prediction horizon of 120 s) cross-track contract deviations along with their ±2 standard deviation confidence intervals (dashed red lines).

an adaptive statistical time series framework. The performance of the methods has been assessed via simulation. In present conformance monitoring, conformance quality has been monitored via a statistical tool, and it has been shown that an alarm is issued instantaneously following the introduction of a detrimental (abnormal) event. In future contract conformance monitoring, the adaptive statistical time series method has been shown to provide an alarm of non-compliance (with probability 0.95) 27 s before a corresponding scheme based on a nominal probabilistic method. Current research focuses on various improvements and extensions of the adaptive statistical time series framework.

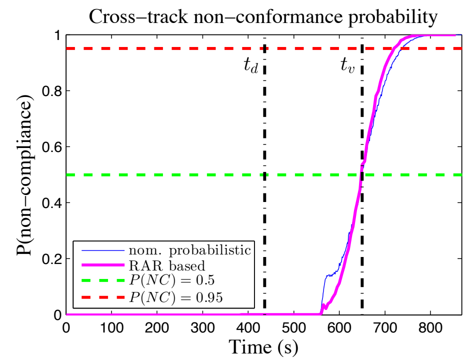

Fig. 6. Probability of future non-conformance for the cross-track contract deviations versus flight time for both the nominal probabilistic and adaptive statistical time series methods (prediction horizon of 120 s).

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