OPTIMAL PREDICTION OF ADVERSE EVENTS IN AVIATION DATA

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The prediction of anomalies or adverse events is a challenging task, and there are a variety of methods which can be used to address the problem. In this paper, we demonstrate how to recast the anomaly prediction problem into a form whose solution is accessible as a level-crossing prediction problem. The level-crossing prediction problem has an elegant, optimal, yet untested solution under certain technical constraints, and only when the appropriate modeling assumptions are made. As such, we will thoroughly investigate the resilience of these modeling assumptions, and show how they affect final performance. Finally, the predictive capability of this method will be assessed by quantitative means, using both validation and test data containing anomalies or adverse events from real aviation data sets that have previously been identified as operationally significant by domain experts. It will be shown that the formulation proposed yields a lower false alarm rate on average than competing methods based on similarly advanced concepts, and a higher correct detection rate than a standard method based upon exceedances that is commonly used for prediction.

Developing an automated anomaly prediction capability in near-real time for aircraft systems or subsystems is of great importance for the future of aviation safety. It is also important that algorithms providing this predictive capability are capable of isolating the anomalies to specific components or sensors, while providing an algorithmic explanation of the reasons why the anomalies were flagged. One of the objectives we plan to achieve in the process of developing such an algorithm is to allow for the prediction to occur within a 2 second time horizon of an actual adverse event, with a false positive rate less than 5%. The motivation for these specific objectives stems from the need to establish a minimum required time for the crew to respond to a critical event with a high level of confidence, in part driven by a study performed by Hayden *et al.*[1]. The operational significance and meaning of the adverse events will be assessed by domain experts, but can also be assisted by appropriate tools such as limit checks and other well established universally accepted aviation rules.

These types of specifications fit very neatly within a framework introduced in previous work [2], where we developed the theoretical basis for a method of optimal level-crossing prediction, enabled by Kalman filtering. Optimality is realized here by providing an upper bound on the false alarm probability for a fixed detection probability, and over a fixed prediction horizon. Therefore, it is our aim in this paper to document our initial steps towards achieving the goal of developing a new, state-of-the-art forecasting technology by using these newly conceived theoretical ideas. Our hope is to demonstrate the plausibility of these novel techniques by conducting a preliminary investigation using real aviation data. In previous optimal level-crossing prediction research, we studied a "two-sided" level crossing event that spans a fixed prediction horizon and exceeds upper and lower predefined critical thresholds symmetric about the mean of a stationary linear Gaussian process many times during the timeframe. The two-sided case is practically relevant when monitoring residuals that may be derived from the output of other machine learning algorithms or transformed parameters that relate to system performance. This last point is of paramount importance in the use of this approach.

In this investigation we will test the theoretical assumptions made by appealing to the use of the optimal level-crossing predictor and other standard unsupervised machine learning techniques

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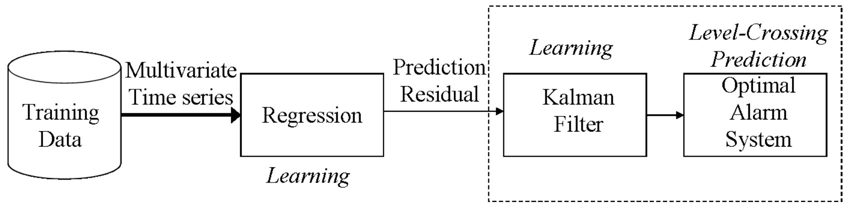

FIGURE 1. Proposed Functional Architecture

used to parameterize the underlying models shown in Fig. 1. Here we will employ real aviation data sets, where independent time series each represent individual flights. Selected sets of flights will be chosen to develop a model, and two other distinct sets of flights from this same aircraft will be used for validation and testing purposes. We appeal to the idea of "boosting" in order to allow for the use of the residual generated from the base model by the Kalman filter. In Fig. 1, the regression block represents the base model, which processes a select number of parameters (the "multivariate time series") and maps them to a distinct target parameter. The residual output from this block quantifies the difference between the actual value of the pre-specified target parameter and the value predicted by the base model. Thus, implicitly the use of this architecture extends the domain of this work to systems producing multivariate data, rather than only univariate data as was introduced in the seminal article for this topic. This is primarily implemented with the use of a "base model" to preprocess the multivariate time series, resulting in a univariate output.

Ostensibly, this mapping should have a functional basis specific to the safe operation of the aircraft, for which any reasonably robust machine learning approach can be used (*e.g.* linear regression, quadratic regression, Gaussian process regression, nonlinear kernel-based regression such as is found in MSET [3] (Multivariate State Estimation Technique), bagged neural nets, *etc.*). However, for the purposes of our study, we will use support vector regression (SVR, [4]) to provide this mapping. Furthermore, a single target parameter that acts as a global health indicator which represents safe operation of the aircraft rarely exists in reality. In fact, there may be multiple such indicators for each adverse event or anomalous operation that is a candidate for prediction. Thus, we may train as many support vector regressors as there are available to characterize adverse events and target parameters. However, in this study we draw from a pool of candidate target parameters and use only a single target parameter for a single adverse event based upon a selected performance objective.

The residual may hypothetically be distributed in such a way that is amenable to modeling as a Gaussian distribution, and can be used as the basis for learning a linear dynamical system, which can subsequently be used for design of an optimal level-crossing predictor. As such, we will investigate the two-sided level-crossing event in this paper, and also use a Kalman filter-based approach in an optimal manner relevant for the prediction of level-crossings. Note that the optimal level-crossing predictor in its current incarnation requires use of the underlying linear dynamical system model associated with the Kalman filter (evidenced by the arrow leading from the Kalman filter box to the optimal alarm system box within the dotted line shown in Fig. 1).

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