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Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring

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ABSTRACT

Safety is key to civil aviation. To further improve its already respectable safety records, the airline industry is transitioning towards a proactive approach which anticipates and mitigates risks before incidents occur. This approach requires continuous monitoring and analysis of flight operations; however, modern aircraft systems have become increasingly complex to a degree that traditional analytical methods have reached their limits – the current methods in use can only detect 'hazardous' behaviors on a pre-defined list; they will miss important risks that are unlisted or unknown. This paper presents a novel approach to apply data mining in flight data analysis allowing airline safety experts to identify latent risks from daily operations without specifying what to look for in advance. In this approach, we apply a Gaussian Mixture Model (GMM) based clustering to digital flight data in order to detect flights with unusual data patterns. These flights may indicate an increased level of risks under the assumption that normal flights share common patterns, while anomalies do not. Safety experts can then review these flights in detail to identify risks, if any. Compared with other data-driven methods to monitor flight operations, this approach, referred to as ClusterAD-DataSample, can (1) better establish the norm by automatically recognizing multiple typical patterns of flight operations, and (2) pinpoint which part of a detected flight is abnormal. Evaluation of ClusterAD-DataSample was performed on two sets of A320 flight data of real-world airline operations; results showed that ClusterAD-DataSample was able to detect abnormal flights with elevated risks, which make it a promising tool for airline operators to identify early signs of safety degradation even if the criteria are unknown a priori.

1. Introduction

Historically, accident prevention efforts focused on accidents analysis: a particular event was investigated in detail; measures were developed to prevent the event from reoccurring. These efforts led a steady improvements of aviation safety over the past 60 years (Boeing Commercial Airplanes, 2014). However, safety remains a key element in air transportation, a colossal industry which moves 3.1 billion passengers a year (International Civil Aviation Organization, 2014). Mishaps still

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happen, and if they do, often make headline news globally. To further improve an already respectable safety performance, the aviation industry is transitioning towards a proactive approach. Different from previous ones, the proactive approach aims at continuously monitoring flight operations and identifying risks; mitigation measures are taken before incidents occur. Data, especially the use of sensor data, are the key to facilitate this transition.

Among others, data from the Flight Data Recorder (FDR) or Quick Assess Recorder (QAR) onboard every aircraft are the most promising. Thousands of technical parameters are recorded throughout a flight, airspeed, altitude, pitch, roll, engine parameters, etc. The dataset contains rich information about the aircraft system, the external environment, and pilot operations. Major airlines have implemented a Flight Operational Quality Assurance (FOQA) program or Flight Data Monitoring (FDM) program to archive and analyze these flight data from daily operations (Federal Aviation Administration, 2004). Current analysis tools are all based on the Exceedance Detection (ED) (Federal Aviation Administration, 2004), a method which can identify undesired events by checking if particular flight parameters exceed a pre-defined limit under specified conditions. The adjustment of ED is costly because parameter thresholds depend specifically on aircraft types, flight phases, airport conditions, and flying procedures, etc. A key limitation of ED is that one needs to pre-define what to look for in advance; and the pre-defined criteria, which are derived from finite historical incidents, can never predict future risks arising from infinite operational variances and emerging new technologies. A number of studies have discussed the limitations of a pre-defined list (Matthews et al., 2013; Tsuruta, 2009).

Recent studies focused on the development of data-driven methods that monitor operations continuously for road and rail transportation using in-vehicle data recorders or network sensors (Chang et al., 2008; Li et al., 2014; Shi and Abdel-Aty, 2015; Shichrur et al., 2014; Toledo et al., 2008; Zhang et al., 2011). Studies focusing on air transportation are sparse. The Morning Report software package was one of the earliest efforts made to detect anomalies from routine flight data as part of NASA's Aviation Performance Measurement System (APMS) (Amidan and Ferryman, 2005). The software models time series data of selected flight parameters using a quadratic equation. Each flight, mapped as a point, is described by the coefficients of the quadratic equations in the feature space. The distance between this point and the mean of the distribution in the feature space, is used to compute an "atypical score" for each flight. Some studies, the Inductive Monitoring System (IMS) software (Iverson, 2004) for instance, adopt a semi-supervised learning approach that summarizes the data distributions of typical system behaviors from a pre-sanitized training dataset. The typical data distributions are then compared with real-time operational data to detect abnormal behaviors. However, the IMS is limited in its ability to account for temporal patterns and it cannot function without a training dataset. Others adopt the unsupervised approach. The Sequence Miner algorithm focuses on discrete flight parameters to monitor pilot operations, such as cockpit switch flips (Budalakoti et al., 2008, 2006). The algorithm can discover abnormal sequences in the switch operations based on the Longest Common Subsequence (LCS) measures. To incorporate both discrete and continuous flight parameters in FDR data, Srivastava develops a statistical framework that discretizes the continuous flight parameters in pre-processing steps (Srivastava, 2005). Built on this framework, Das et al. develop the Multiple Kernel Anomaly Detection (MKAD) which combines both continuous and discrete parameters via kernel functions and applies one-class Support Vector Machine (SVM) for anomaly detection (Das et al., 2010). MKAD assumes there will always be a single, consistent data pattern for normal operations. This assumption does not hold in real practice. One example is that both Instrument Landing Systems (ILS) approaches and visual approaches are standard operations in landing; yet the procedures of these two approaches are different from each other, so are their data patterns. Further, how to characterize the temporal structure during various flight phases remains unresolved. Matthews et al. summarize the knowledge discovery pipeline for aviation data using these algorithms discussed above (Matthews et al., 2013). A common challenge exists for all the above methods: standards of norm are not easy to define in practice – real-world flight operations are too complex to be assumed to have one standard pattern, or to be represented by a limited set of training data.

A thorough literature review concluded that despite a vast number of techniques developed in cluster analysis and anomaly detection in general (Chandola et al., 2009; Hodge and Austin, 2004; Jain et al., 1999), no existing technique is directly applicable to solve the anomaly detection problem for flight operations.

In this paper, we developed a data mining-based approach (referred to as ClusterAD-DataSample) to support proactive safety management in air transportation. In this approach, we apply a Gaussian Mixture Model (GMM) based clustering to digital flight data in order to detect flights with unusual data patterns. These flights may indicate an increased level of risk under the assumption that normal flights share common patterns. ClusterAD-DataSample is built on another anomaly detection method, ClusterAD-Flight, developed by the authors (Li et al., 2015, 2011). However, ClusterAD-Flight can only detect abnormal flights during take-off or approach as a whole, rather than instantaneous abnormal data samples during a flight. Compared with other data-driven methods to monitor flight operations, ClusterAD-DataSample can (1) better establish the norm by automatically recognizing multiple typical patterns of flight operations, and (2) pinpoint which part of a detected flight is abnormal. With this method, airline safety experts will be better equipped to monitor flight operations by detecting flights with unusual data patterns, and locate abnormal behaviors from everyday operations even if the criteria for anomalies are unknown a prior.

In this paper, "anomaly" and "abnormal flights" means flights with unusual data patterns, which differs from "unsafe flights" and "risky flights." Flights with abnormal data patterns are of interest for detection, but they need to be reviewed by safety experts to determine whether they represent any safety risks.