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Feature Extraction and Synchronization from Multi Sensor FDR Data Strea

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Abstract

Modern aircraft generate massive volumes of heterogeneous data through distributed onboard sensors that continuously monitor flight dynamics, propulsion systems, navigation, environmental conditions, and aircraft health. Effective utilization of these multi-sensor Flight Data Recorder (FDR) streams requires advanced methodologies capable of extracting meaningful features while ensuring accurate temporal synchronization across diverse sensor sources. This chapter presents a comprehensive overview of contemporary techniques for feature extraction and synchronization in multi-sensor FDR data analytics, emphasizing their significance in aviation safety, accident investigation, predictive maintenance, and intelligent flight monitoring. The discussion encompasses flight data acquisition architectures, preprocessing strategies, normalization and standardization methods, event-based feature representation, advanced signal processing approaches, transformer-based representation learning, Kalman filter-based synchronization, and multi-sensor data fusion techniques. Machine learning and deep learning models are examined for automated feature learning and intelligent interpretation of high-dimensional flight data, enabling improved anomaly detection, fault diagnosis, flight phase identification, and operational performance assessment. Current challenges associated with heterogeneous sensor integration, asynchronous data streams, missing observations, computational scalability, and real-time processing are critically analyzed alongside emerging developments in edge computing, explainable artificial intelligence, and digital twin technologies. The chapter provides a unified framework that supports the development of reliable, scalable, and data-driven aviation safety systems, offering valuable insights for researchers, aviation engineers, and industry practitioners engaged in next-generation flight data analytics.

Keywords: Flight Data Recorder (FDR), Multi-Sensor Data Fusion, Feature Extraction, Temporal Synchronization, Transformer-Based Learning, Aviation Safety Analytics.

Introduction

Modern aviation has experienced a profound technological transformation driven by advancements in digital avionics, intelligent sensing technologies, and integrated aircraft management systems. Contemporary commercial and military aircraft function as highly interconnected cyber-physical systems capable of continuously monitoring every aspect of flight operations through extensive networks of onboard sensors [1]. Flight parameters associated with engine performance, flight dynamics, navigation, structural integrity, environmental conditions, hydraulic systems, electrical subsystems, fuel management, and flight control mechanisms are continuously measured and transmitted throughout every phase of flight [2]. These measurements are collected by the Flight Data Acquisition Unit (FDAU) and securely stored within the Flight Data Recorder (FDR), creating a comprehensive historical record of aircraft operations. Initially developed to support post-accident investigations, Flight Data Recorders have gradually evolved into strategic information repositories supporting aircraft performance evaluation, operational efficiency analysis, predictive maintenance, fault diagnosis, and intelligent safety management [3]. Rapid growth in sensor deployment and improvements in recording technology have significantly increased both the quantity and diversity of flight data generated during routine aircraft operations. Modern aircraft routinely record hundreds to thousands of operational parameters at varying sampling frequencies, producing complex multivariate time-series datasets that capture dynamic interactions among numerous aircraft subsystems. Such technological progress has shifted aviation analytics from conventional manual inspection toward intelligent data-driven methodologies capable of extracting valuable operational knowledge from continuously expanding Flight Data Recorder datasets [4]. This evolution has established multi-sensor flight data as one of the most valuable resources for improving aviation safety, enhancing aircraft reliability, optimizing operational performance, and supporting the development of intelligent decision-support systems within modern aerospace engineering [5].

The continuous expansion of aircraft sensing capabilities has introduced significant analytical challenges because operational data originate from heterogeneous sensors characterized by different physical principles, communication protocols, measurement units, temporal resolutions, and sampling frequencies [6]. Navigation systems continuously record aircraft position, altitude, velocity, heading, and attitude information, while propulsion monitoring systems capture rotational speed, exhaust gas temperature, fuel consumption, oil pressure, compressor performance, and vibration signatures [7]. Flight control systems generate measurements associated with actuator positions, pilot control inputs, trim adjustments, and aerodynamic control surfaces, whereas environmental monitoring equipment records atmospheric pressure, outside air temperature, humidity, wind velocity, and icing conditions. Structural health monitoring sensors contribute additional measurements describing strain, fatigue, vibration, and stress experienced by critical aircraft components during operation [8]. Every subsystem generates information according to its operational requirements, producing asynchronous sensor streams that differ considerably in update intervals, numerical ranges, and communication timing. Variations in sensor calibration, transmission latency, clock synchronization, measurement precision, and environmental disturbances introduce additional complexity into Flight Data Recorder datasets [9]. Noise, missing observations, sensor drift, communication interruptions, and inconsistent recording intervals frequently reduce data quality, making direct analytical processing unsuitable for reliable aviation applications. Effective utilization of heterogeneous multi-sensor flight data therefore requires comprehensive preprocessing methodologies capable of cleaning, synchronizing, normalizing, and integrating diverse measurements before meaningful feature extraction and intelligent analysis become possible. Robust preprocessing establishes the foundation upon which reliable aviation analytics, operational diagnostics, and safety assessment systems can be developed [10].