Towards an embedded system for failure diagnosis in drones using AI and SAC-DM on FPGA

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***Abstract*—We present a way of failure detection in real-time unmanned aerial vehicles (UAVs) by integrating Chaos Theory and AI techniques on an FPGA board. The *Signal Analysis based on Chaos using the Density of Maxima* (SAC-DM) validates the input of the *Machine Learning* (ML) model due to the relation between the density of maxima and autocorrelation length. While the accuracies achieved solely by SAC-DM are not remarkably high, the ML model demonstrates an accuracy of 92.46% when utilizing sac-dm results as inputs. The unprecedented integration of SAC-DM on FPGA board serves as a solution for high-speed onboard processing, parallel integrated data synchronization and fusion, and an enhanced low-power architecture.**

***Index Terms*—Failure detection, Real-time, UAVs, Chaos Theory, FPGA boards.**

I. Introduction

Advancements in flight control systems, particularly in Unmanned Aerial Vehicles (UAVs) or drones, underscore the critical need for real-time failure detection to ensure heightened safety and reliability. In the past, various methods have been employed to address this need. Notably, a novel approach involving the analysis of data from accelerometers has been proposed. This analysis applies chaos theory and stochastic processes, transforming the sensor's noisy signal into easily identifiable waves. More specifically, this work expands on a previous study that introduced the innovative technique called SAC-DM [1], initially introduced in physics [2]. The SAC-DM technique can reveal patterns arising from the chaotic behavior of different systems, such as brushless DC motors [1] and biological systems [3]. Although this technique exhibits high accuracy in failure detection through the parameterization of chaos, it has proven to be limited in diagnosing failures [4]. This limitation must be addressed, as detecting a failure is as crucial as understanding its severity.

ML has demonstrated precise anomaly detection [5], relying on sensors such as vibration for anomaly detection. However, the complexity of the relationship between input and classification is directly proportional to the size of the ML model. Consequently, the computational expense of inference in the ML model increases as more types of failures are considered.

***F**ield **P**rogrammable **G**ate **A**rrays* (FPGAs) emerge as a suitable platform for evaluating ML model with low power and high-performance requirements. By situating the processing system near the source of inputs, i.e., the sensors, storage and communication overheads are eliminated. Simultaneously, various programmable designs for FPGAs showcase low-energy inference in hardware [6].

Recent works, focusing on weight-stationary implementations, demonstrate high-throughput, low-resource inference architectures for FPGAs [7]. These architectures can fully exploit the FPGA Logic-Block structures [8].

Challenges and limitations exist for SAC-DM in real-time Failure Detection, including a low acquisition rate and asynchronous data. Increasing the acquisition rate from multiple accelerometers is a challenging task that could enhance classification accuracy. However, it necessitates correct synchronization among data streams from various sensors, posing a particular difficulty in sequential processors. Achieving accurate synchronization of multiple sensors is crucial for the accuracy of fusion algorithms [9].

To overcome these challenges and bolster the efficacy of SAC-DM in real-time failure detection for drones, we advocate integrating a ML model onto a FPGA. The proposed FPGA-based solution addresses identified limitations through high-speed onboard processing, parallel integrated data synchronization and fusion, and an enhanced low-power architecture.

II. SAC-DM

In this study, we propose employing SAC-DM for real-time detection and quantification of various failure conditions in Unmanned Aerial Vehicles (UAVs). The initial step involves acquiring a dense dataset to apply SAC techniques, utilizing data collected through accelerometer measurements from a Tarot-RC 690 model UAV [10]. Chaotic signals are derived from three accelerometers symmetrically positioned in three out of the six arms of the UAV, with a sampling frequency of 1KHz.

The raw data comprises chaotic signals encompassing approximately 350×10^3 points, gathered over a 25-minute flight period, encompassing take-off and landing. Employing a capture frequency of 1KHz, we organize the dataset into intervals of $N = 1000$ points, representing 1-second windows. Initially, we compute the SAC-DM signal $S_{\mathrm{DM}}(\omega_i) = n_i/M$, where ω_i, n_i, and M denote the i-th window of size N, the number of peaks in the window, and the total number of windows, respectively. The length of the SAC-DM array, denoted as M, is determined by dividing the total number of points by the window size N ($M \approx 350 \times 10^3/1000 = 350$ windows).

Subsequently, we partition the data into training and testing sets, compute the average and standard deviation of the SAC-DM signal, and employ them for signal classification into four categories: Normal (N) condition and three failure

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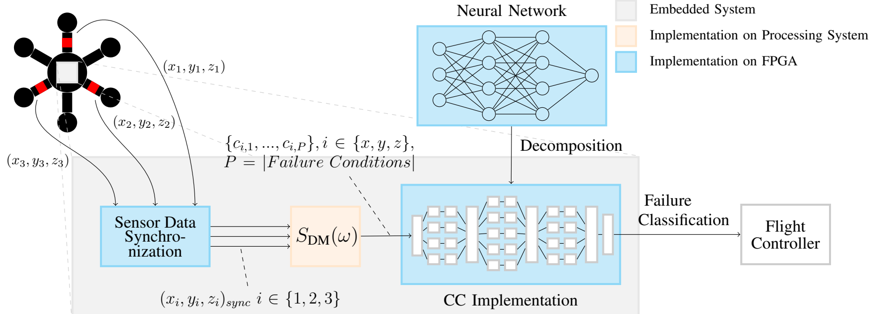

Fig. 1. Overview of the proposed design using SAC-DM for failure detection and classification in conjunction with ML.

conditions. These failure conditions correspond to failures detected on the propeller at the adjacent sensor arm (FC1, FC2, FC3). The resulting accuracy for failure diagnosis using SAC-DM is 24.65%, 17.07%, and 21.35% in the x, y, and z-axes, respectively. The achieved accuracies by SAC-DM are not notably high, and external factors such as wind or weather, coupled with the limitation imposed by a low data acquisition rate, may influence these results.

III. ML and SAC-DM on FPGA

A combined approach is suggested, employing SAC-DM for anomaly detection and ML model structures for anomaly classification. Various metrics derived from the captured sensor input data can serve as inputs for the ML classifier. Utilizing the aggregated data processed by SAC-DM, the sensor input is segmented into $t = 1\,\mathrm{s}$ windows. Our design utilizes these windows to compute signal averages, deviations, and maxima amplitudes. The anomaly classifier is then implemented through a lightweight Multi-Layer Perceptron based on these metrics.

With limited battery capacity on drones, FPGA provides high performance with low power requirements for inference [11], being an energy-efficient alternative to GPUs. Here we can add a big picture of our idea, showing the main architecture and how SAC-DM and ML will work together on an FPGA. The SAC-DM will produce as output the SAC-DM itself, its average, and its variance. Our approach to anomaly classification leverages SAC-DM as input and an MLP as the classifier, as depicted in Fig.(1).

Component	S	P	LUTs	`CARRY8`
Fully Connected Layer 1	2	2	1124	106
Fully Connected Layer 2	2	2	1689	154
Fully Connected Layer 3	3	2	2136	207

Component	LUTs	FFs	f (MHz)	P_{dynamic}	P_{static}
Overall MLP	4943	706	150	294 mW	593 mW

TABLE I
SYNTHESIS RESOURCES AND SLICES WIDTH S AND NUMBER OF FACTORS P OF ALL MATRIX MULTIPLICATIONS OF THE OVERALL MLP.

The weights of a trained MLP can be considered as constant. This enables weight-stationary implementations of the network. Using FPGAs, novel methods achieve efficient yet flexible implementations, encoding the weight matrices directly within the architecture itself [7]. By leveraging this Computation Coding approach and FPGA-specific optimizations to the architecture design [8], we achieve an efficient implementation. Table I gives an overview of resource utilization of an implementation of an MLP classifier for the presented problem of detecting bearing faults targeted at the `xczu7ev-ffvc1156-2-e`. Further, all implementations of CMMs leverage ternary input adders [8] at $8\,\mathrm{bit}$, i.e. an approximation error of at most $48\,\mathrm{dB}$. A pipelined implementation with registers between each layer achieves $150\,\mathrm{MHz}$, i.e. classification can take place with 150 Mfps. The trained network predicts the ten anomalies with 92.46% accuracy.

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