Advanced machine learning for the detection of single event effects

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***Abstract*—With the increase of component complexity, protection against single event effects becomes a critical point for the dependability of space systems. In this paper, machine learning is investigated to improve the detection of radiation faults. An algorithm named DYD^2 that meets space application requirements is proposed. In addition, a study to improve the characterisation of single event effects through feature extraction is described. Finally, results of experimentation based on a heavy-ion campaign test are discussed.**

***Index Terms*—Artificial intelligence, Machine learning, Single event effects, Space radiations, Anomaly detection, Electronic applications**

I. Introduction

In the last decades, the growth in computation power has evolved significantly. This led to applications becoming more complex and to many technological breakthroughs. However, due to the harsh environment in space, the space industry used to need time to integrate those breakthroughs and catch up. Nonetheless, with the advent of SpaceX and the successful launch of its reusable launcher Falcon9 in 2010, the space industry is taking a new trajectory known as the *new space* era. Use of *Components Out of The Shelf (COTS)* has known a massive increase in space applications. The lowered price of space missions was followed by a massive increase in satellite launches per year, as well as the number of mission failures [1].

Single Event Effects (SEEs) represent faults induced in electronic components by highly energetic particles collisions. Sensitive parts of components are called *sensitive nodes* [2]. When a SEE occurs in a component, the last line of defence is a threshold-based anti-latch-up system. However, non-destructive SEEs like single event functional interrupt or micro latch-up hidden in the nominal behaviour are not detected by such a system. Therefore, extensive research is performed to improve the detection of single event effects [3].

In a previous work, the possibility to use artificial intelligence algorithms to improve the baseline detection method of single event effects is discussed [4]. The main conclusion of this work is that, even though learning algorithms could not replace the baseline anti-latch-up system for destructive hard errors, they are relevant for the detection of non-destructive and hidden faults. From there, a new algorithm called *Dynamic Double anomaly Detection (*DYD^2*)* is developed to meet the space industry requirements [5].

This paper presents the application and results of the machine learning algorithm DYD^2 on experimental tests performed. In section II, a brief presentation of DYD^2 is given. Section III reports the experimental setups composed of californium-252 and laser testing on an ATMEL SAM3X8E. Section IV presents a discussion about the adequate features to characterise single event effects efficiently. Finally, section V describes the results of DYD^2 on experimental data.

This work was granted by the CNES and Région Occitanie.

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II. DYD^2 algorithm

A. Anomaly detection specifications in space applications

Space applications impose many constraints that machine learning algorithms generally do not meet. Therefore, the machine learning algorithm DYD^2 has been designed to detect single effects in space missions while satisfying the requirements below:

1) Change point anomaly detection in time series: The algorithm must be able to detect anomalies in data sets that take the form of time series. Those anomalies are defined as anomalous change points in the time series. In a space application, anomalies can be considered as high current events in the supply current. Moreover, the detection algorithm should be able to detect critical and destructive SEE, such as single event latch-up, accurately. Finally, it must be able to detect soft errors that can pass through the baseline anti-latch-up system. DYD^2 is specifically designed to handle time series. Furthermore, a change point detection followed by a two-phase anomaly detection algorithm enables DYD^2 to detect anomalous behaviours.

2) Low memory usage: The algorithm must be able to be embedded and run on minimal resources. Indeed, some space missions are designed for microcontrollers with only a few Kbytes of flash memory, and available memory space must be optimised as much as possible. DYD^2 is based on specific objects called μ-clusters that group together similar samples. Therefore, only the μ-clusters need to be stored in memory, instead of the entirety of the data set, drastically decreasing memory usage.

3) Real-time detection: The algorithm must be able to run efficiently in real-time in regards to the capability of space components. DYD^2 uses a fast change point detection to classify new samples as potential anomalies. Doing so avoids processing non-anomalous data points, thus saving time. Also, the μ-clusters design accelerates the detection process. Indeed, fewer objects need to be addressed as opposed to the entirety of the data set.

4) Adaptability in evolving environment: The algorithm must be able to adapt to a constantly changing environment. Indeed, due to the *total ionising dose*, a component behaviour evolves during the entirety of the mission. These evolutions modify significantly the supply current, so any training performed beforehand becomes irrelevant. By the use of an update phase that is constantly adapting to incoming data, DYD^2 is able to follow the deviation of a data set and does not require additional training for that.

5) Training on normal behaviour only: The training phase must be performed using only normal data. Indeed, the simulation of single event effects can be tedious and complex, and removing the need for extensive radiation testing is crucial. It is complicated to get an extensive database of all possible anomalies for complex components, such as a microcontroller. Therefore, the database can only be partially created, and so the quality of the prediction of a machine learning algorithm can be severely altered. DYD^2 is part of a sub-field of machine learning called *one-class classification*, in which only one type of data is needed to create a model: data of the normal behaviour.

6) Interpretability: Finally, the last requirement to consider is linked to the nature of artificial intelligence fiels and the apparition of *black-box* models. The algorithm must be as much interpretable, or explainable, as possible. It is well-known that it is complicated to determine precisely how a deep learning algorithm gives a specific prediction. In the case of space application, the possibility to interpret the prediction seems essential to apply with confidence machine learning detection for radiation faults. It is why tools such as neural networks are not investigated in this work. DYD^2 is a deterministic algorithm. Its predictions are not based on probabilistic measurements. Also, the evaluation of an anomaly is based on explicable tools such as the notion of reachability and μ-clusters. Finally, tools are developed to visualised the evolution of DYD^2 through a data set, giving the possibility to explain its predictions.

B. DYD^2 *overview*

Following these specifications, a new machine learning algorithm is designed. Called Dynamic Double anomaly Detection (DYD^2), most of its principles are described in [5]. Therefore, only a quick summary will be done here based on Fig. 1.

First, training is performed using normal data of the component 1 . The objective is to determine a model able to represent the normal behaviour of the component. Therefore, this data must match the ones monitored during the mission. Training is performed prior to the beginning of the space mission and constitutes the *offline phase* of DYD^2. From there, two maps are created: an *outer map* and an *inner map*. These maps represent the model of the component.

After training, the *online phase* begins. DYD^2 works as a two-phase anomaly detection algorithm. It distinguishes the notion of *outer features* and *inner features*. Prior to these two detection phases, a change point detection is performed 2 . Doing so avoids processing all data that does not correspond to high current events.

The first detection phase 3 uses what is called *outer features*. It consists of raw quantities that are quick to process. This phase aims to detect critical and heavily out of distributions anomalies qualified as *outer anomalies*.

The second detection phase 4 uses *inner features*. Unlike outer features, the inner features are created by performing deeper analysis, such as statistical or frequency analysis, on incoming data. It aims at detecting subtle anomalies hidden in normal behaviour called *inner anomalies*. To do so, a waiting period is needed to gather enough data to create inner features. As this phase focuses on non-critical faults (as critical anomalies are detected in the previous phase), the waiting period does not endanger the component.

Finally, an update phase 5 is performed on both the outer and inner maps. These updates allow following the most recent data, therefore adapting to incoming deviation without the need for new training.

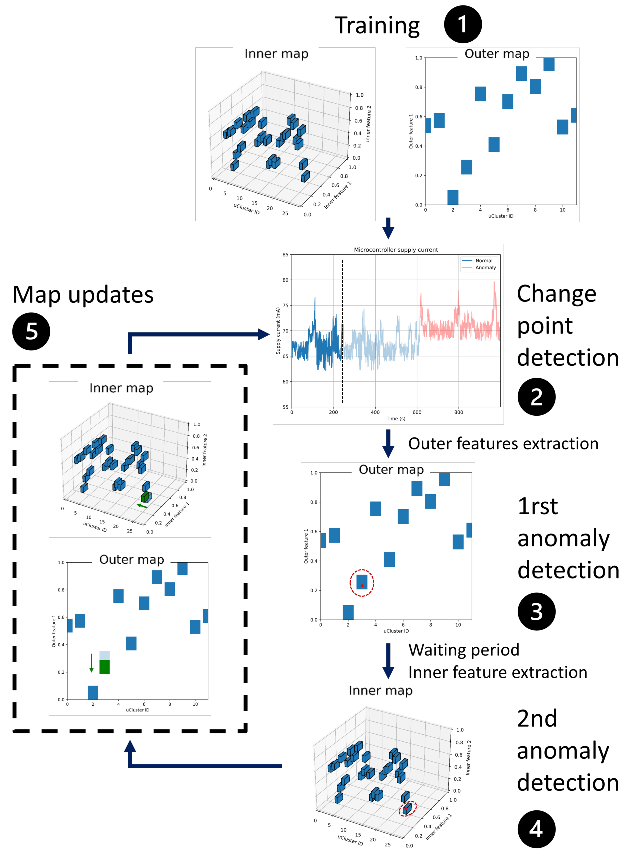


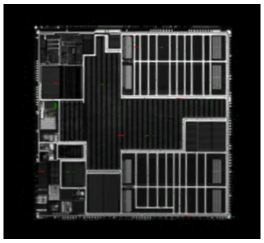
Fig. 1: Anomaly detection with DYD^2

III. EXPERIMENTAL DETAILS

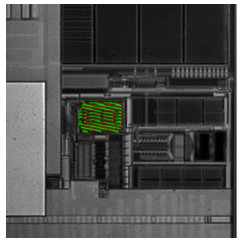
A. ATMEL SAM3X microcontroller

This study is focused on the ATMEL SAM3X8E. It is based on the ARM Cortex-M3 processor designed for low-cost and energy-efficient integrated circuits. The preparation of the chip was to remove the protection on the frontside using plasma technic. Three reasons led to choose the ATMEL SAM3X over other microcontrollers:

1) The SAM3X family of microcontroller is used in various projects across the space industry (such as the ANGELS project).
2) The ATMEL SAM3X8E version is used as a central component for the widely distributed Arduino DUE development board. Choosing an Arduino DUE board



(a) Optic 1x



(b) Optic 20x

Fig. 2: Laser picture of the SAM3X8E

removes the need to design a whole new testing board, and gives access to a quick setup to test the microcontroller functionalities.

3) The component has to be sensitive to radiation in order to get failure examples in the study. Indeed, studies show that even the rad tolerant version, the SAMA3X8ERT, is sensitive to non-destructive single event effects [6].

B. Californium-252 and laser testing

To emulate single event effects, Californium-252 (Cf252) and laser tests are performed. For both tests, a protection device is set up at 250mA. The Cf252 LET is around 42 MeV.cm²/mg at the surface of the chip. The test facility is located in TRAD Tests & Radiations in Labège, France. The total irradiation time is 5200s. The whole process is monitored every 10ms. Examples of soft errors are detected.

Laser testing is performed at the CNES laser facility equipped with a class 1 laser linked by a specific software on a dedicated computer. The characteristics of the laser are given table I. Due to the impossibility of getting access to the backside of the chip with Arduino DUE board, tests are performed on the front side of the chip. With laser testing, it is possible to get an image of the chip by scan process (see Fig. 2). It enables the possibility to aim precisely at any sensitive areas that are discovered during tests. One of them is highlighted in green in Fig. 2b.

Many high current events are recorded during the experimental tests. When a high current event that is below the threshold is detected, a manual power cycle of the board is performed. Most of the time, the supply current gets back to its normal behaviour (see Fig. 3).

Wavelength	Max pulse freq	Power	Optics	Scan axis
1064nm	20MHz	≈600mW	1x, 5x, 20x	X, Y

TABLE I: Laser characteristics

IV. FEATURE EXTRACTION AND SELECTION

The features are the information used as input by the machine learning algorithm to perform the prediction. Therefore, feature selection is a crucial step. In the case of single event effect, the monitored data consists of time series of various indicators such as supply current, supply voltage or device temperature. In this study, efforts are focused on the supply current, as it is the most common indicator in single event effects evaluation.

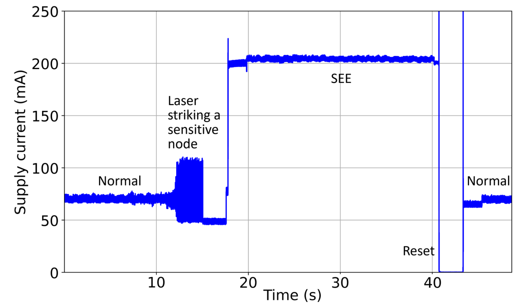


Fig. 3: Power cycle example

In this context, the first step to introduce artificial intelligence in the detection of radiation faults is to discover which attributes must be chosen or built to discriminate between normal and potential degraded behaviours during a single event effect.

The data sets gathered through Cf252 and laser testing are the ones used for the feature selection. Therefore, the remarks given in the following sections are valid for both experiments. Moreover, it is important to note that this preliminary study is heavily application-dependant. Nonetheless, we believe that the features described in this section are still relevant in any application aiming to characterise SEEs.

A. Statistical features

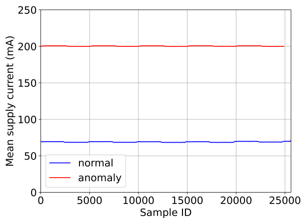
Statistical evaluation is a classic treatment in data analysis. The statistical analysis is done by moving multiple samples gathered in a time window across the data set and then computing the statistical features of that time window. This way, statistical features are calculated for each sample of the data set.

In this study, many features were considered, but only a small part that gave a good characterisation of a single event effects are kept:

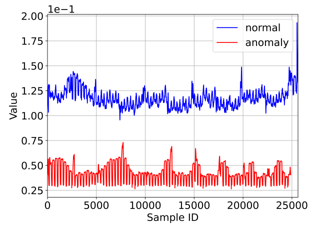
- The mean: For persistent anomaly, a shift of the signal mean is a relevant indicator (see Fig. 4a). However, if the mean shift is small enough, it can be tedious to discern the anomaly from the normal behaviour.
- The variance: The variance is heavily affected by the mean shift induced by a heavy ion. Therefore, a local increase of the variance can be a symptom of a single event effect.
- The standard error of the mean and the median absolute deviation: These two criteria are chosen due to analysis regarding the impact of a single event effects on the microcontroller functionalities. Indeed, in failure mode, multiple functions can be disabled. Therefore, this loss of activities reverberates through the supply current profile (see Fig. 4b).

B. Frequency features

The frequency spectrum of the supply current can be obtained with *discrete Fourier transform (DFT)*. Once this treatment is done, a spectrum comparison is performed between normal behaviour and anomalous data sets. (see Fig. 5).

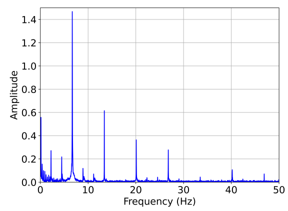


(a) Mean value

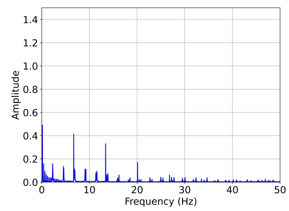


(b) Standard error of mean

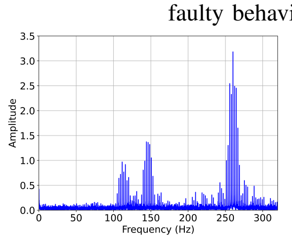
Fig. 4: Statistical features



(a) Frequency spectrum for normal behaviour



(b) Frequency spectrum for faulty behaviour



(c) Frequency spectrum during a laser pass on a sensitive node

Fig. 5: Frequency spectrum

It is important to note that these results only consist of a preliminary study on limited data sets. Indeed, an extensive study by multiplying radiation condition tests is needed to precisely define the impact of single event effects on the frequency spectrum.

In this study, the frequency value corresponding to 0Hz is removed as the amplitude of this peak is way greater than the others. In addition to the lack of information given by this peak, it rendered the readability of other values impossible. Fig. 5a and Fig. 5b correspond respectively to the frequency spectrum of the behaviours before and after the occurrence of a single event effect. Noisy peaks appear when the component is in one failure mode. Moreover, it can be observed a significant decrease in the prominent peaks (8 Hz, 12Hz, 20Hz and 28Hz) compared to the same frequencies of the normal behaviour. When the laser is pointed at a sensitive node, a very specific spectrum emerges (Fig. 5c). The presence of multiple peaks in the higher range of frequencies is systematic during these experiments. Further studies need to be done to unearth the cause of this phenomenon.

V. DYD^2 RESULTS ON HEAVY-ION TESTING

In [5], only results performed with computer simulations are presented. In this article, new results of DYD^2 on experimental data provided by the CNES are discussed (see Fig. 6).

The data set comes from a series of heavy ion tests performed in the UMCG- PARTREC facility on a BS62LV4006 CMOS. The sampling time of measures is fixed to 10ms,

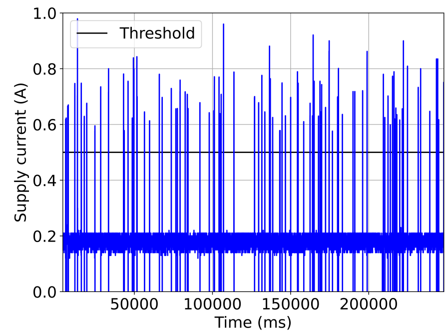


Fig. 6: Test data set provided by the CNES

and the detection threshold is set to 500mA. A little bit less than 25000 samples were recorded during these run tests, and a hundred events were captured by the threshold detection device. Then, DYD^2 is run through the entire dataset to compare its efficiency with the baseline threshold method.

During this test, DYD^2 detects a total of 115 anomalies. All peaks exceeding the threshold of 500mA are classified as outer anomalies. Therefore, it can be noticed that DYD^2 performed as good as the baseline detection method. Furthermore, most of the 15 left potential anomalies detected can be referred to as soft errors, as the component behaviour seems to deviate from normal condition, and return to normal after the next power cycle.

Moreover, DYD^2 is tested on on-board conditions with the help of an Arduino Due equipped with a SAM3X8E in charge of the detection tools. This board monitored the device under test during the whole experiment. Thanks to the three-steps detection, the microcontroller is able to process all the data in real-time showing that DYD^2 is perfectly compatible with embedded applications.

VI. CONCLUSION

This paper proposes an implementation of machine learning for the detection of single event effects. Specifications for space missions are discussed. A feature selection is proposed for single event effects characterisation. Finally, the algorithm is tested on a data set coming from heavy ion test campaign. Several points need to be investigated in the future as an extensive study of the frequency spectrum, and the performance analysis of DYD^2 relatively to false positive.

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