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Unsupervised machine learning application to identify single-event transients (SETs) from noise events in MOSFET transistor ionizing radiation effects

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A R T I C L E I N F O

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A B S T R A C T

This article presents a novel application of the k-means unsupervised machine learning algorithm to the problem of identifying single event transient (SET) events from noise during heavy-ion irradiation experiments of an electronic device. We explore the performance of the k-means algorithm by analyzing experimental datasets of SET events produced by several heavy-ions irradiations of a MOSFET transistor. Data anomalies and effectiveness of the chosen features (mean, standard deviation, skewness, and kurtosis) were investigated using the Isolation Forest and Random Forest algorithms, respectively. The results show a high capability of the K-means algorithm to identify SET events from noise using the first four statistical moments as features, allowing in the future the use of this method for in situ event detection and diagnosis without previous algorithm training or pre-analysis of the experimental data.

1. Introduction

The growing use of semiconductor devices in harsh environments has intensified studies on the reliability of the data generated by such electronic systems and on how ionizing radiation could affect these circuits [1], taking direct account of the devices' new applications, including aerospace technology and computers under work uninterrupted. These effects become more expressive in environments where radiation exposure is intense, such as satellites, particle accelerators, nuclear reactors, and medical equipment, among others [2].

Ionizing radiation absorbed in semiconductor devices can change their characteristics, modify electrical parameters, and even lead to complete failure of the component [3]. In particular, the constant miniaturization of devices has motivated several studies to be carried out to verify the importance of the effects of ionizing radiation on circuits, which in the past could even be considered negligible [4].

The effects induced by radiation in electronic circuits can be distinguished as cumulative or stochastic, while the errors caused by them can be of two types: hard-errors, which permanently compromise the component, or soft-errors, associated with a change in the information stored in the circuit [3]. The stochastic effects are the so-called single event effects (SEE).

The SEE is caused mainly by high LET (linear energy transfer) particles, e.g. heavy ions, and it is characterized by the deposition of large amounts of energy in a small volume of material, leading to the creation of a high density of charge carriers in that region. Heavy ions can interact in different ways when penetrating the material, such as through nuclear reactions (generating radiation emission and reaction products) and ionization of the atoms, and a single heavy ion can produce an amount of charge greater than that of several protons, photons, or electrons, which is conventionally called the "single event" effect. In an analog device, a single event transient (SET) is characterized by a transient effect that propagates through the entire circuit [4–6], which can lead to a current pulse or, in a logic circuit, a single event upset

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(SEU), that changes the value stored in a register/memory position [7].

A way to test a device's SET sensibility is to irradiate it with heavy ions produced by a particle accelerator [3] and detect those events in the format of a pulse using an oscilloscope. In principle, a simple voltage level discrimination could be used to identify those events, but this process can lead to false pulse detection if noise sources are present, which is usually the case. As the SET cross-section and thus failure-in-time (FIT) rate are directly affected by the number of recorded events, one needs to remove any event that was not caused by the incident particles. This task can be done by event-by-event inspection, Fourier filtering, signal matching, or discrimination by remarkable signal characteristics, such as rise time, fall time, amplitude, and so on [8].

A promising alternative solution to remove the noise events in the dataset is to use Machine learning (ML) algorithms since they can detect statistical patterns and regularities in data. Most of the ML applications in Physics [9–12], however, are done by supervised algorithms, which means that the algorithms need previously analyzed training samples with a set of input variables to map the features that will allow making predictions of unknown datasets. This approach may not be useful for removing noise events from SET datasets because it would require analyzing part of the acquired dataset with traditional techniques to create a training dataset to properly apply the supervised algorithm. Since different noise and event types can occur depending on the ion beam, the electronic device, and the experimental setup, a new training dataset must be created for any new experiment. Clustering unsupervised ML algorithms, however, are suitable to be applied to remove noise events without the support of traditional techniques since they do not need previously analyzed samples once they use features such as mean and standard deviation of the input data to classify it by its similarities.

This work presents a methodology for automating the identification of the SET events from noise using an unsupervised machine learning k-means algorithm [13]. The first four statistical moments (mean, standard deviation, skewness, and kurtosis) are used as features to compose a four-dimension dataset, and k-means labels are then used to separate the signals. Those features were evaluated by using a supervised random forest regression algorithm [14] to verify the contribution of each individual feature in the clustering of the experimental data. Anomalies in the data sets were also investigated by using an unsupervised machine learning Isolation Forest algorithm [15].

2. Material and methods

2.1. The SET event datasets

The SET event datasets were obtained by irradiating a p-type MOSFET, model 3 N163, with several ion beams and energies, which can be seen in Table 1. The experiments were realized in the SAFFIRA facility [16] located at the 8UD Pelletron accelerator of the University of São Paulo, Brazil. In this experiment, ions from the 8MV tandem accelerator were scattered through gold foils to reduce beam intensity and irradiate the device with adequate flux. The energy loss in the gold foils was accounted for, and the effective energy values on the device are presented in Table 1. The MOSFET was decapsulated and placed in a vacuum chamber and polarized with V_{DS} = -0.1 V and V_{GS} = -4.5 V, thus operating in the linear response region. The device's drain was connected to the 50 Ω input of a 5GS/s digital oscilloscope, which recorded the occurring transient signals during irradiation. Although the oscilloscope's trigger was adjusted at each irradiation, it was kept at lowest possible value to acquire several different signals without too much noise. The dataset is available from the corresponding author upon reasonable request.

These SET datasets have a total of 65,641 events mixed between SET events and noise signals that triggered the oscilloscope. Fig. 1 shows an example of a SET event (in blue) and a noise event (in red) in the ^{16}O experiment, while Fig. 2 shows the total mean signal of this experiment. Noise events must be removed before a mean event can be calculated and the effects of the heavy-ion beam studied. One can note in Fig. 2 how noise events distorted the mean signal making it difficult for automated analyses of the peak area and, consequently, to identify the heavy-ion energy deposition in the electronic device.

Table 1
Ion beam, beam energy, effective beam energy, surface LET and number of total events (a mix between SET and noise events) collected in each experiment.

Ion beam	Beam energy (MeV)	Effective beam energy (MeV)	Surface LET (MeV·cm^2/mg)	Total number of events
^{16}O	42	40.2	5.0	14,997
^{16}O	62	60.5	4.1	19,998
^{12}C	52	50.8	2.2	2499
^{19}F	70	68.2	5.4	9999
^{28}Si	78	72.2	16.6	9999
^{35}Cl	42	36.3	18.1	2999
^{35}Cl	56	50.1	17.6	598
^{48}Ti	78	70.0	23.8	999
^{63}Cu	93	83.0	30.4	2499
^{107}Ag	110	95.6	46.0	1054

2.2. The machine learning algorithms

This section provides a short overview of the machine learning algorithms and libraries used to evaluate SET events from noise. In essence, the unsupervised machine learning algorithm k-means [13] defines clusters by finding the better position of a corresponding centroid based on the squared Euclidean distance between the data

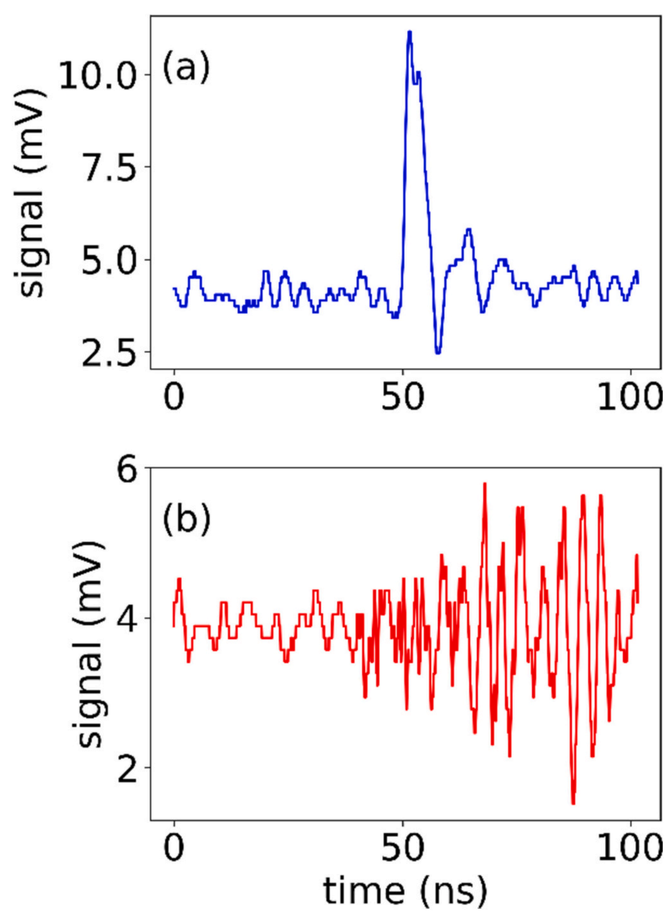

Fig. 1. An example of (a) a SET signal (blue) and (b) a noise signal (red) in the ^{16}O experiment.

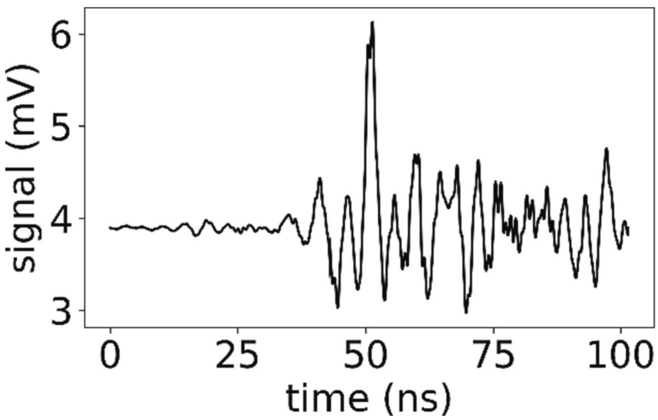

Fig. 2. Mean signal of all ^{16}O SET event dataset.

points. To perform this task, the k-means algorithm starts with *k* centroids randomly selected from the dataset. Then it iterates two steps: first, it assigns data points to the nearest centroid based on the squared Euclidean distance, and second, it updates centroids by taking the mean of all data points assigned to a particular cluster. This two-step iteration is repeated until the centroid positions stop changing. The first four statistical moments (mean, standard deviation, skewness, and kurtosis) were chosen as features since they are the simplest features to be calculated for each event. Fig. 3 shows the features in a 3D color scatter plot for the ^{16}O experiment, and it is possible to see that the dataset has two clear clusters, which we expected are the noise and the SET events.

To investigate the results obtained with the k-means algorithm, we used the Isolation Forest [15] and the Random Forest [14] algorithms to verify anomalies and the effectiveness of the chosen feature set, respectively. The Isolation Forest is also an unsupervised algorithm that creates binary decision trees to separate the data until isolating it from other points. This isolation process is performed through random thresholds steps, and points that need few or many steps (nodes) to be isolated from the others, compared to the general average, are considered anomalies.

Similarly, the supervised algorithm Random Forest is based on many simple decision trees. These trees are composed by nodes and each node is a rule that indicates how to separate events based on a single feature. By the end of the nodes inside a tree, events with similar features will end up in the same set. The nodes with the rules to classify events need to be trained in order to decrease the impurity, which is a measure for quantifying the decision tree separation errors [17].

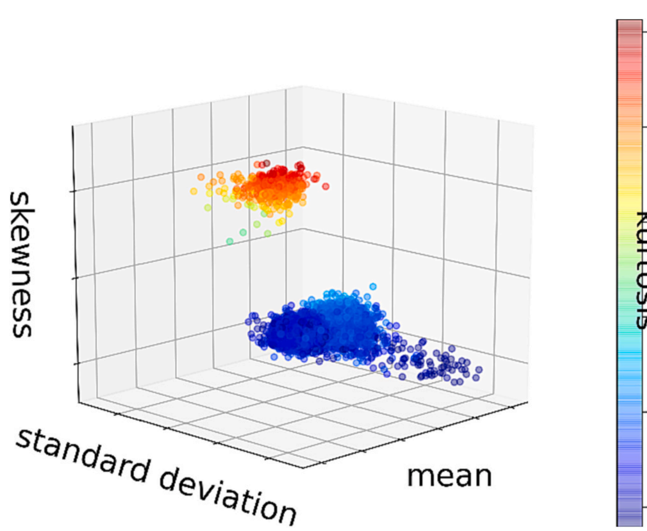

Fig. 3. Features used to cluster the ^{16}O dataset. The 3D axes show the first 3 statistical moments (mean, standard deviation, skewness), and the kurtosis are shown in the color points. All values are in normalized units.

In this work, we used the SCIKIT LEARNING [18] python library to provide the machine learning algorithms. We use SCIPY.STATS [19] python library to perform these moments calculations. The chosen features (mean, standard deviation, skewness, and kurtosis) were L^2 normalized [20], which means that the normalized feature vector has the square root of the sum of the squared vector values equals one. The other program functions were provided by the NUMPY, PANDAS, and MATPLOTLIB python popular libraries, while GOOGLE COLAB was used to execute the codes online.

3. Results and discussion

After using the k-means algorithm, we obtained the labels of each event and the centers of the two clusters. Fig. 4 shows the features of the events allocated in two clusters (red and blue) separated into two scatter plots for ^{16}O (42 MeV), ^{12}C, and ^{35}Cl (56 MeV) ion beams as examples. The clusters displayed in Fig. 4 show how the algorithm could identify and separate SET from noise events for several different conditions, even though the number of events in each cluster is very disproportionate. In the experiment with ^{12}C, there are few SET events (17) against many noise events (2482), and the opposite happens with ^{35}Cl (461 SET events and 38 noise events). Such characteristics were expected because ^{12}C is a lighter ion and deposits little energy in the device and, consequently, produces a SET of amplitude as low as that of the noise's amplitude, while the opposite happens with ^{35}Cl. For the ^{16}O, an intermediate ion, the algorithm found 471 SET events and 4528 noise events.

Fig. 4 also shows that direct analysis by a single feature would be unfeasible because the centers of the clusters change their value for each ion, making separation impossible using thresholds, for example. As the implemented algorithm groups the events by similarity, considering all the four features at once, it proves to be robust for cases where one or two features would shuffle the events as happened with the standard deviation in the experiment with ^{16}O.

To verify if the algorithm separated the SET events from the noise events, we show in Fig. 5 the mean signal of each cluster. The method's capability presented in this work can be verified by comparing Fig. 5 signals with the ones presented in Fig. 1. The separation between the SET and the noise events made the SET events mean much clearer, showing the success of the method. Further, this method can be used in any event dataset and offers the possibility of in situ event detection and diagnosis.

The analysis of the 65,641 total events by the k-means algorithm detected 35,103 SET events. However, for the ^{19}F, ^{35}Cl (42 MeV), ^{48}Ti, ^{63}Cu, and ^{107}Ag ion beams, the algorithm indicates the presence of only one SET event cluster, with few outliers scattered around it. To check if those outliers are really part of the SET events or noise events that the k-means algorithm was not able to identify, we considered those outliers as anomalies and used the Isolation Forest unsupervised algorithm to find and separate anomalies in the dataset. Fig. 6 shows the data and anomalous events detected for the ^{19}F and ^{107}Ag ion beams using the Isolation Forest algorithm, which classifies as anomalous events the points that needed a few or more steps to be isolated from the others, compared to the general average. However, when we analyze the average signal of anomalous and non-anomalous events, as shown in Fig. 7, it is possible to see that the classified anomalous events are also formed by SET events, indicating the reliability of the analysis performed using the k-means algorithm. The reason for ^{19}F, ^{35}Cl (42 MeV), ^{48}Ti, ^{63}Cu, and ^{107}Ag ion beams runs do not present noise events is that for heavy ions, the pulse is high enough to increase the voltage level of oscilloscope discrimination (trigger) above the noise. The exception is the ^{19}F, which was acquired in a low-noise lab environment condition.

Finally, we analyze the effectiveness of the chosen feature set using the Random Forest supervised algorithm to learn the pattern identified by k-means in each beam dataset. We used the k-means clusters as the

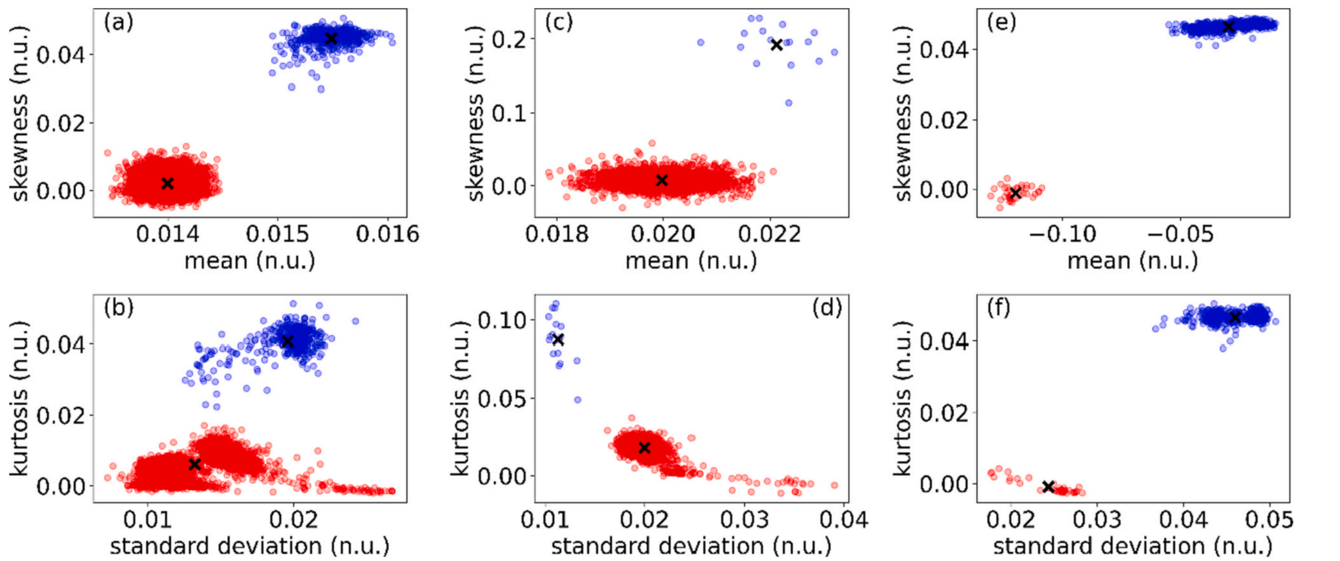

Fig. 4. Skewness x mean plot for (a) ^{16}O, (c) ^{12}C, and (e) ^{35}Cl ion experiments, and kurtosis x standard deviation plot for (b) ^{16}O, (d) ^{12}C, and (f) ^{35}Cl ion experiments. Colors (red and blue) represent the cluster where every event was classified. Black crosses mark the centers of clusters. All values are in normalized units.

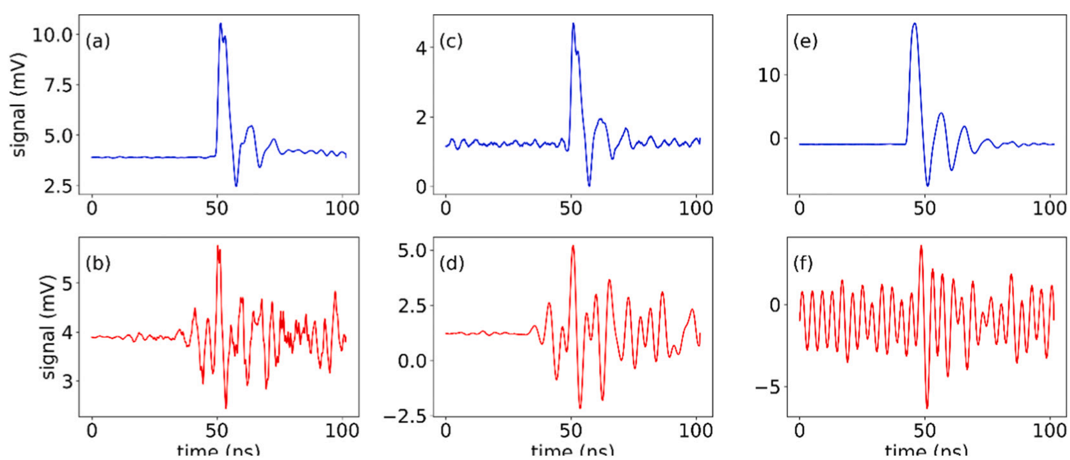

Fig. 5. K-means separated mean signal by cluster one (blue) for (a) ^{16}O, (c) ^{12}C, and (e) ^{35}Cl ion experiments, which identifies the SET events and by cluster two (red) for (b) ^{16}O, (d) ^{12}C and (f) ^{35}Cl ion experiments, which identifies the noise events.

Random Forest training dataset to estimate the importance of each k-means' feature (mean, standard deviation, skewness, and kurtosis) by calculating the average of the impurity reduction over all the decision trees. The result for all ion beams that presented two clusters can be seen in Fig. 8. One can see that generally, all features have a relevant role in the classification, with the highest moments (skewness and kurtosis) being the most important. However, considering each beam individually, as seen in Table 2, some of the features are irrelevant, as seen for the standard deviation feature for the ^{16}O ion beam.

Because of the simplicity of the code, runtimes are satisfactory. We tested the code in an Intel Core i7-4500U CPU with 8 Gbytes of Ram. The average time to cluster a complete run is 1748 ms, which is mostly the time for calculating the mean, standard deviation, skewness, and kurtosis of each event (1710 ms). Once clustering is performed, the prediction for a new single event takes only about 20 μs.

4. Conclusions

In this work, we present an application of unsupervised machine learning algorithms to identify SET events when ionizing radiation effects spectroscopy is applied in an electronic device. We used the k-means clustering algorithm with the first four statistical moments (mean, standard deviation, skewness, and kurtosis) as features to identify SET events from noise events that were high enough to trigger the acquisition oscilloscope. The results indicate that the algorithm could identify and separate SET from noise events for several different conditions, even though the number of events in each cluster is very disproportionate.

In the cases where only one cluster was identified by the k-means algorithm, the results were tested by using the unsupervised Isolation Forest algorithm, which supported the k-means' classification of events as SET events.

The supervised Random Forest algorithm was used with the k-means clusters as the training dataset to verify the effectiveness of the chosen feature set, indicating that all the chosen features are important to generally classify the SET events obtained by heavy ions, but in some cases, as the ^{16}O ion beam, for example, the standard deviation is useless. The suppression of the standard deviation in the feature set, however, does not significantly decrease the code running time and unless ^{16}O was being analyzed alone, this feature contributes to separate the SET events in a big dataset produced using different ion beams.

To conclude, the results obtained using the k-means unsupervised

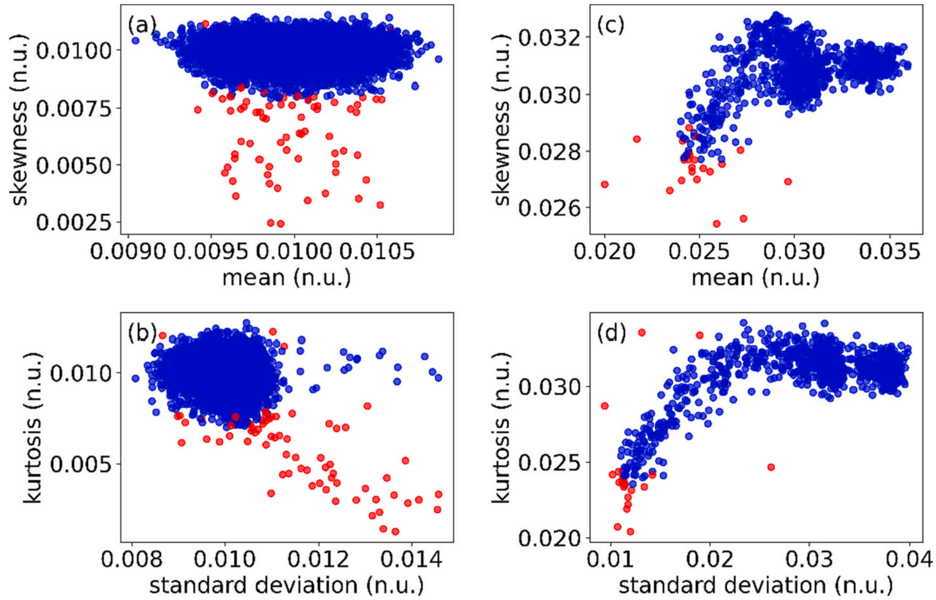

Fig. 6. Skewness x mean plot for (a) ^{19}F and (c) ^{107}Ag ion experiments, and kurtosis x standard deviation plot for (b) ^{19}F and (d) ^{107}Ag ion experiments. Colors (red and blue) represent anomaly and non-anomaly classified events. All values are in normalized units.

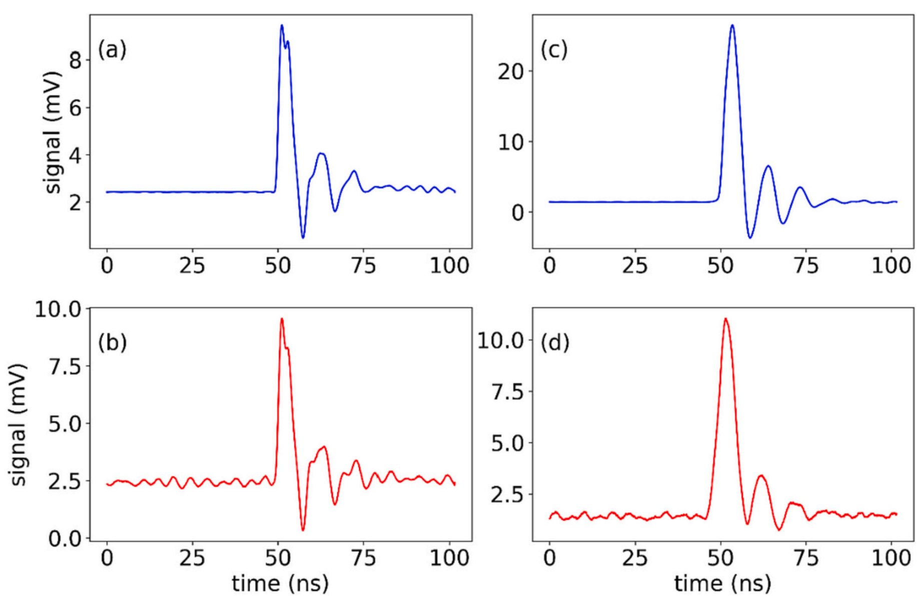

Fig. 7. Isolation Forest separated non anomaly mean signal of (a) ^{19}F and (c) ^{107}Ag ion experiments, and anomaly mean signals (b) ^{19}F and (d) ^{107}Ag. Even the anomaly events can be identifies as SET events.

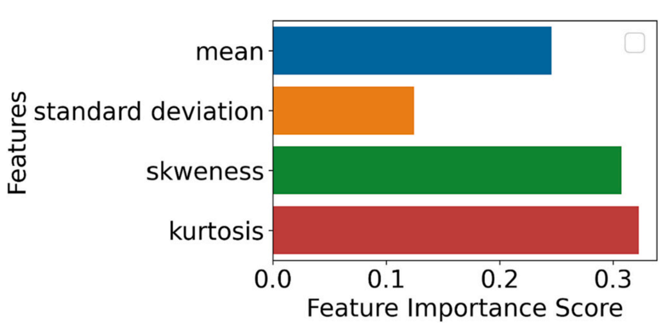

Fig. 8. Feature importance score considering the dataset of all ion beams that presented two clusters.

Table 2
Feature importance score for each ion beam with a cluster of noise events.

Ion beam	Feature importance score				
	^{16}O at 42 MeV	^{16}O at 62 MeV	^{12}C at 52 MeV	28Si at 78 MeV	^{35}Cl at 42 MeV
Mean	0,28	0,17	0,19	0,33	0,24
Stand. dev.	0,01	0,00	0,23	0,21	0,24
Skewness	0,34	0,45	0,24	0,30	0,27
Kurtosis	0,36	0,39	0,33	0,16	0,25

algorithm are promising despite the simplicity of the used features (mean, standard deviation, skewness, and kurtosis). This method is quite simple and fast from a computational point of view, and the findings presented herein offer the possibility of in situ event detection and diagnosis since the applied method does not use example signals (training datasets) to learn the shape of a SET and a noise event.

CRediT authorship contribution statement

Paula R.P. Allegro: Conceptualization, Investigation, Validation, Writing – original draft. **Dennis L. Toufen:** Methodology, Formal analysis, Software, Writing – original draft. **Vitor A.P. Aguiar:** Investigation, Writing – review & editing. **Lucas S.A. dos Santos:** Methodology, Writing – review & editing. **William N. de Oliveira:** Methodology, Writing – review & editing. **Nemitala Added:** Investigation. **Nilberto H. Medina:** Investigation. **Eduardo L.A. Macchione:** Investigation. **Saulo G. Alberton:** Investigation. **Marcilei A. Guazzelli:** Investigation. **Marco A.A. Melo:** Investigation. **Juliano A. Oliveira:** Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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