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Deep Learning-Based Process for the Automatic Detection, Tracking, and Classification of Thermal Events on the In-Vessel Components of Fusion Reactors

Erwan Grelier^{1,2,*}, Raphaël Mitteau², Victor Moncada²

¹*Aix Marseille Univ, CNRS, Centrale Marseille, Institut Fresnel, Marseille, France*

²*CEA, IRFM, F-13108 Saint Paul-lez-Durance, France*

**Corresponding author: erwan.grelier@cea.fr*

This paper presents an automated process that detects, tracks, and classifies thermal events using infrared movies of the inside of the vessel for machine protection. This process relies on a Region-Based Convolutional Neural Network, a deep learning model, for the detection of thermal events in infrared images. This model is trained using a dataset of thermal events, obtained by manually annotating thermal events in movies from the WEST tokamak, which is equipped with 12 infrared cameras that provide information about the surface temperature of the in-vessel components. The labels characterizing the thermal events are chosen in a custom-designed ontology, which is being developed.

This automated process can correctly detect, track and classify most of the regular thermal events appearing in the infrared movies of WEST, in a manner compatible with the real-time plasma operation. These events can be used for post-pulse analysis by deriving from them metadata, displayed in a dedicated dashboard, that help human operators understand better and more quickly what happened during a pulse.

Keywords: Machine protection; Artificial intelligence; Deep learning

1. Introduction

The ability to analyze thermal events occurring on the internal components of fusion reactors during their operation is important both for machine protection and for science. The large quantity of data generated by diagnostics during the operation of long-pulse machines makes it cumbersome for humans to cope with the real-time analysis of thermal events. There is a strong need for a process able to detect and analyze thermal events automatically and in real-time, for feedback control and investment protection.

This paper presents an automated process that detects, tracks, and classifies thermal events using infrared movies of the inside of the vessel. This process relies on deep learning models [1], trained on a specially created dataset of thermal events. A web-based dashboard displays the most critical thermal events detected automatically by the process, to help the machine monitoring team to take action between pulses, if necessary.

The dataset of thermal events is obtained by manually annotating thermal events in movies from the WEST tokamak, which is equipped with 12 infrared cameras that provide information about the surface temperature of the in-vessel components [2].

This paper is structured as follows: Section 2 presents the thermal events dataset, which contains all the knowledge used to train the automated process, briefly described in Section 3. Section 4 shows results obtained with this process using dedicated key performance indicators. Section 5 details the dashboard that displays the most critical thermal events detected. Finally, Section 6 presents the conclusions and outlook of this work.

2. Formalization of knowledge in a thermal events dataset

Supervised deep-learning models learn from example: given couples of inputs and expected outputs, the parameters of the model are learnt for it to perform a specific task, without having to properly formalizing it. Here, the automated process needs to detect thermal events in the frames of infrared movies. This means that, to train the model, many infrared images (the inputs) must be gathered, with the corresponding thermal events manually annotated on the images using bounding boxes (the expected outputs). All these data constitute what is called a dataset, which is then partitioned in three parts: the train split, used to learn the parameters of the model; the validation split, used to select the values of the hyper-parameters associated with the training; and the

test split, used to evaluate the performance of the trained model.

The dataset is constituted of 88 manually annotated infrared movies of the interior vessel of WEST, provided by its infrared thermography diagnostic [2]. It contains movies from three types of lines of sight (divertor: 31 movies, lower-hybrid antenna: 31 movies, and wide-angle: 26 movies), and from pulses from the C4 and C5 campaigns of WEST. The training, validation and test splits contain 53, 17 and 18 movies respectively. The pulses have been chosen to maximize the variety in the types of experiments, to have movies as different from each other as possible. Table 1 presents the repartition of the different classes of thermal events in the dataset. The classes are selected in a simple custom-designed ontology, currently in development. A short description of each class can be found in [3]. The label “hot spot” is the catchall class, which gathers all the thermal events that do not belong to any other class in the ontology. This explains why it represents more than half the events in the dataset.

Table 1: Repartition of the classes of events in the dataset.

Label (class)	Number of thermal events	Proportion
hot spot	867	54%
outboard strike point	232	14%
inboard strike point	228	14%
ion ripple losses	16	0.99%
radiated heat flux	12	0.74%
electron type 1	234	15%
reflection	23	1.4%
Total	1612	100%

The manual annotation of infrared movies is a cumbersome task, which presents risks of inconsistencies between annotators. To mitigate these risks, annotation tools are developed and regularly improved; they decrease the annotation time and the inconsistencies. To create the dataset, the annotation tool initially described in [3] was improved to reduce the jittering and flickering of the proposed annotations. Figure 1 shows an example of manually annotated frame of an infrared movie of the divertor of WEST.

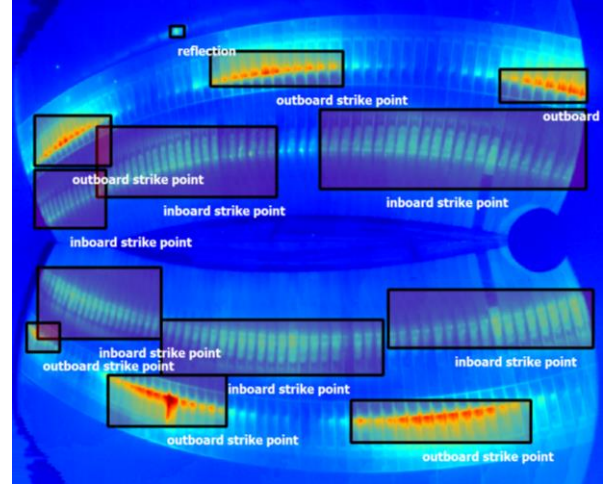


Figure 1: Example of manual annotation of an infrared video of the divertor of WEST.

All the thermal events, either manually annotated or automatically detected, are centralized in a SQL database for easy access and analysis by the machine protection and scientific teams.

3. Automated process for the detection, tracking and classification of thermal events

The automatic detection, tracking and classification of thermal events is handled by the process represented in Figure 2. It takes as inputs a video stream from the infrared (IR) thermography diagnostic of WEST as well as data from other diagnostics (e.g. additional heating, plasma density) and a 3d scene model (the correspondence between the pixels of the movies and the components inside the machine, as well as the associated admissible temperatures, defined in so-called WEST Operation Instruction sheets). The process outputs thermal events detected during the pulse, tracked in time and with a classification label, that can be sent to the Plasma Control System (PCS) for feedback control during plasma operation.

The process is constituted of three stages:

1. Given the infrared video stream as input, the first stage detects, tracks and provides a first classification of the thermal events. To do so, it relies on Faster R-CNN [4] for the detection of thermal events in each frame (implementation of Detectron2 [5] by Meta AI) and on SORT [6] for the tracking of the events between frames.
2. Given the detections of stage 1 as well as the 3d scene model and data from other diagnostics, the second stage will provide a fine classification of the events. To do so, a

deep learning model has to be trained to extract meaningful features from all the inputs and perform data fusion. This stage is to be implemented: the foreseen model architecture is a Fully Convolutional Neural Network [1].

3. Finally, the third stage will use the finely classified thermal events to take action on the pulse using feedback control loops in the Plasma Control System. These loops can be expert rules or can be learnt from example using learning techniques.

Additional detail on the automated process can be found in [3].

Currently, stage 1 is automated, while stages 2 and 3 are performed by the protection officers between pulses, using the detections of stage 1 and the thermal events dashboard, described in Section 5. If necessary, action on the next pulse is taken by the operational team, based on the phenomenological analysis of the thermal events by the protection officers.

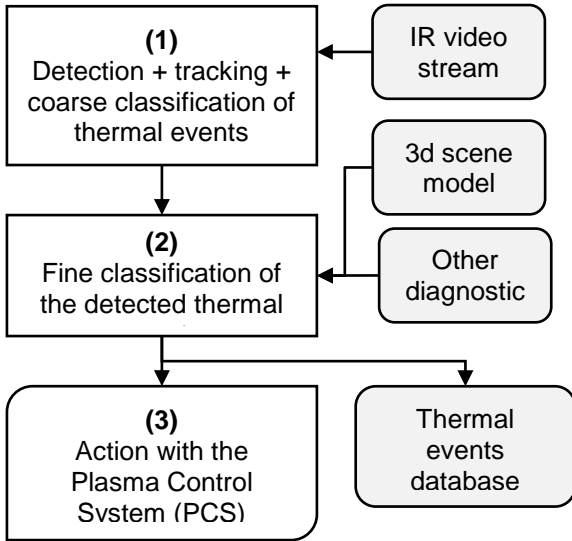


Figure 2: Organigram of the automated process, which is constituted of three stages.

4. Obtained results from stage 1 of the process

Figure 3 shows an example of automatic detection of thermal events in an infrared movie of the wide-angle line of sight of WEST. The process is able to detect the major thermal events present in the scene, in a qualitatively satisfying manner.

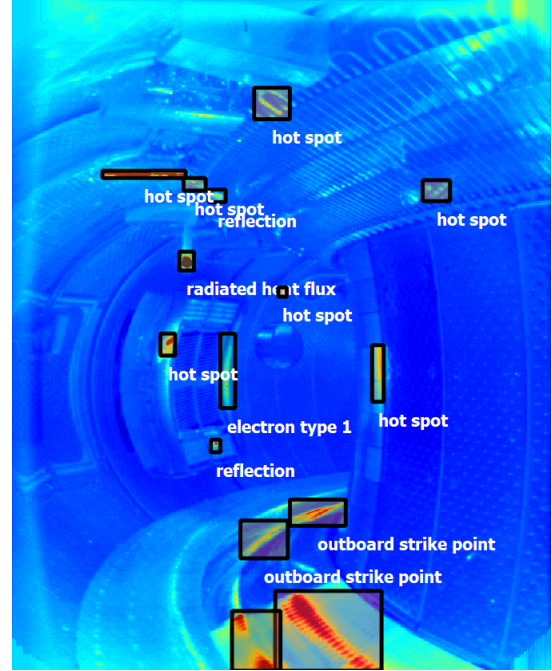


Figure 3: Example of automatic thermal events detection on the wide-angle view of WEST.

The quantification of the performance of the process relies on key performance indicators (KPI) dedicated to the task of object detection, described in [8]. Table 2 presents the results obtained on the test set for the three types of lines of sight considered, using four KPIs: the mean precision, mean recall, mean average precision (mAP), and Spatio-Temporal Tube Average Precision (STT-AP). The precision is the ability of the process to only detect relevant thermal events, whereas the recall is its ability to find all the relevant thermal events. The mean average precision combines the

Table 2: Key performance indicator values obtained on the test set, averaged over all classes, for each type of lines of sight.

Key performance indicator	divertor	lower hybrid antenna	wide-angle	all
$mRecall@0.5$	70.53%	59.05%	71.57%	68.07%
$mRecall@0.75$	46.40%	27.55%	42.47%	37.24%
$mPrecision@0.5$	89.87%	80.82%	76.26%	76.72%
$mPrecision@0.75$	60.59%	38.65%	43.64%	41.63%
$mAP@0.5$	66.19%	54.88%	61.87%	59.70%
$mAP@0.75$	34.26%	14.87%	27.13%	22.82%
$mAP@0.5:0.95$	35.77%	23.19%	31.28%	27.81%
$STT-AP@0.5$	27.86%	30.96%	29.15%	30.29%
$STT-AP@0.75$	13.76%	10.41%	11.80%	11.88%

two notions into one number, by computing the area under the precision x recall curve. Finally, the spatio-temporal tube average generalizes the average precision to videos instead of individual frames. The number next to each KPI represents the selected Intersection over Union (IoU) threshold. For the STT-AP, a generalization of the IoU to spatio-temporal detections is used, called spatio-temporal tube IoU (STT-IoU). The larger the threshold, the more a prediction box must be close to a real box for the prediction to be counted as correct. The mention “0.5:0.95” indicates that the measures were done for values of the IoU threshold in [0.5, 0.95] in steps of 0.05, and then averaged. The column “all” corresponds to the KPIs obtained when combining the detections from all the lines of sight.

The detector gives good performance for relatively low IoU threshold values, and this performance decreases with the increase of the IoU threshold. This behavior is expected, and is actually not critical for thermal events detection. Indeed, for machine protection, the key aspect of a detector is its ability to correctly detect and roughly encompass thermal events; being able to encompass them tightly with a box is secondary, especially when many types of thermal events have fuzzy boundaries, making them hard to annotate precisely and consistently.

Some disparities can be noticed between the lines of sight. They can be explained by the differences

between the thermal scenes and thermal events observed in each view. Indeed, the divertor line of sight contains mainly strike lines, which are large, whereas the lower hybrid antenna line of sight mainly contains many small hot spots. The wide-angle view, which is the most complex thermal scene, contains both large and small objects. Given these results, special care ought to be taken to improve the detection of smaller objects; this is an outlook of this paper. Finally, given an IoU (or STT-IoU) threshold, the difference in performance between the mAP and the STT-AP shows that the tracking algorithm should be improved: this is also an outlook of this article.

5. Dashboard of the most critical thermal events

A web-based dashboard, accessible anywhere at WEST, displays automatically the most critical thermal events detected. It is available to the protection officers in the control room, to help them analyze the thermal events and take action on the next pulse in coordination with the operational team, if necessary for machine protection.

The dashboard, called *ēveniō* (to “happen” or “occur” in Latin), is shown in Figure 4, where the thermal events detected during the last pulse of WEST’s C5 campaign are displayed. The graphical

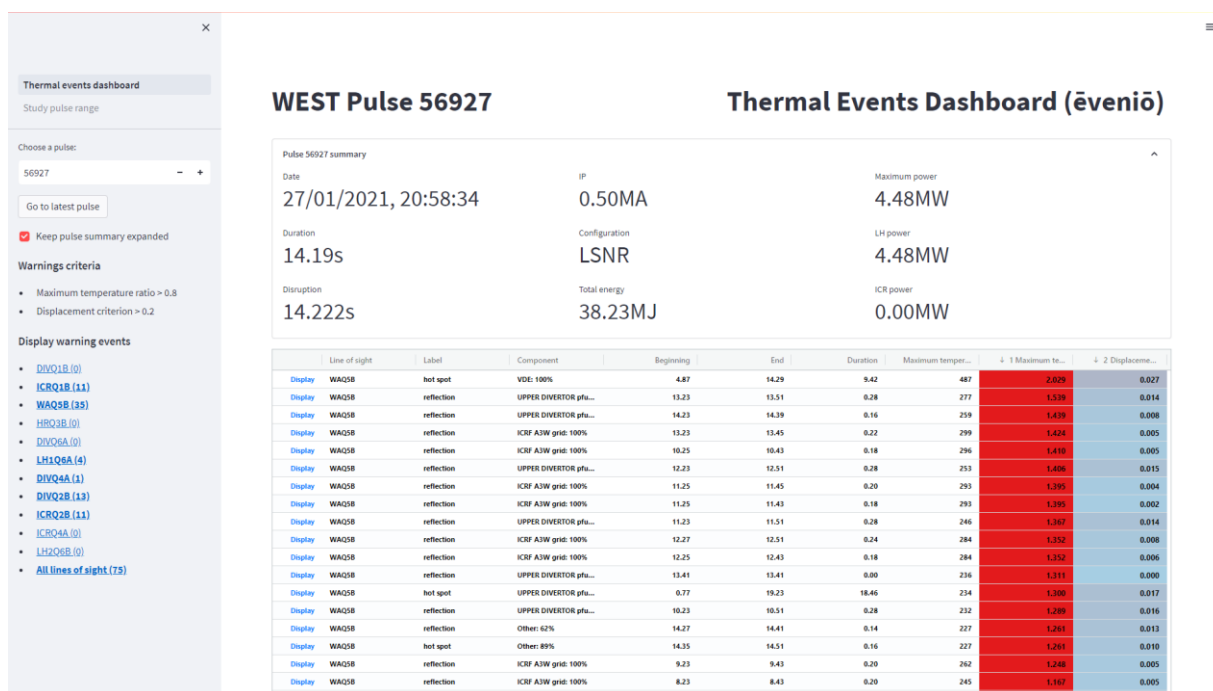


Figure 4: Dashboard display for the pulse #56927 (last pulse of WEST’s C5 campaign).

interface is generated using a Streamlit¹ instance that runs on a local server, and is linked to the centralized SQL thermal events database. The dashboard is interfaced with the visualization software ThermaVIP [7], so that the detected thermal events can be easily visualized, analyzed and modified, relabeled, or rejected if necessary, by displaying them in the software in one click.

Each row of the dashboard corresponds to one detected thermal event. For each event, many metadata are displayed, for instance: a label that characterizes it, the physical component on which it appeared, and the maximum temperature that it reached.

Furthermore, two criteria are displayed (appearing in color on the dashboard): the maximum temperature ratio, and the displacement criterion. The first one is equal to the greatest ratio between the maximum temperature reached by a thermal event and the maximum admissible temperature of the component on which it appeared, defined in the WEST Operation Instruction. The second criterion quantifies the displacement of the thermal event during its life: its aim is to detect abnormal events, such as a sensor that is dislodged from its protective casing. To compute it, the centroid of the thermal event for each timestamp is stored, and the value of the criterion is defined as the greatest Euclidian distance between all the possible pairs of centroids, normalized between 0 and 1 to make it independent from frame size. The dashboard is implemented in a flexible way, so that new criteria can be implemented easily to suit the needs of the users.

These two criteria are used to quantify the criticality of an event. Indeed, when a criterion exceeds user-defined warning thresholds, the associated thermal event is moved at the top of the table and displayed in bold, so that it is highlighted to the protection officers. A color map is used to represent graphically the values of the criteria, with the value being red if it exceeds the warning threshold.

For the computation of the maximum temperature, a small time interval of 0.1s on each side of the disruption (if one occurred) is ignored, because the maximum temperature measured during this brief period is not relevant for machine protection. The disruption time is inferred from the plasma current automatically at the end of the pulse.

The dashboard can be used by the protection officers to provide feedback to other protection

officers or to the developers of the process, by selecting a status for an event. This status can for instance be “Analyzed (follow-up required)” to indicate the need for a follow-up analysis, or “Detection Error” to indicate that the automated process has produced a false positive, in other words a detection that is not a real thermal event.

Furthermore, additional pages can easily be added to the dashboard to perform specific tasks, such as showing statistics on the thermal events that have been detected during a given week. This is for example useful for the weekly reporting meetings that take place during experimental campaigns at WEST.

6. Conclusions and outlook

A process that detects, tracks and classifies thermal events automatically from infrared videos and signals from other diagnostics is presented, in a manner compatible with the feedback control system of fusion machines. This process relies on artificial intelligence and deep learning techniques to learn from example: it then requires the creation of a dedicated dataset, constituted of many manually annotated infrared movies.

Currently, only the first stage (detection, tracking and coarse classification of thermal events from infrared movies) of the process has been implemented and tested on data from the WEST tokamak, with encouraging results, both qualitatively and quantitatively. The implementation of stages 2 and 3 is an outlook of this paper.

A dedicated web-based dashboard is developed, to display the detected thermal events automatically after an experiment. Its aim is to provide an easy to use tool for the officers in charge of machine protection to analyze the thermal events that occurred on the first wall of a fusion machine. It is interfaced with ThermaVIP, enabling the quick visualization of the detected thermal events in the infrared movies. The dashboard is a powerful tool that is highly customizable to suit the needs of the protection and operational teams.

The automated process, the thermal events dataset and the dashboard have been developed and tested on data from previous campaigns of WEST, and are to be continuously improved during its future experimental campaigns. They will also be used on other fusion reactors (W7-X, DTT, ITER,

¹ <https://streamlit.io/>

with simulation and/or experimental data when available) using transfer learning.

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