# Thermal Event Recognition Applied to Tokamak Protection during Plasma Operation

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***Abstract*—Magnetic confinement fusion reactors are complex devices where a large amount of energy is required to make the fusion reactions happen. In such experimental conditions, the Plasma Facing Components (PFC) are subjected to high heat fluxes. In current tokamaks like Tore Supra, infrared thermographic diagnotics based on image analysis and feedback control are used to measure and monitor the heating of the PFC during plasma operation. The system consists in detecting high increase of the IR luminance signal beyond fixed temperature thresholds for a set of predefined Regions of Interest (ROI). Consequently, this system neither takes into account the thermal objects outside of the ROI, nor the geometric information of the detected thermal object. In this paper, we propose a new vision-based approach for the automatic detection of thermal events. This approach is composed of three main tasks: thermal object detection (1), classification (2), and thermal event recognition (3). We present results of our approach for the recognition of one critical thermal event and compare it with the previous system.**

## I. Introduction

Magnetic confinement fusion is a more and more active field of research since nuclear fusion is considered as a promising approach for alternative energy production. One issue to reach a sufficient power balance in the future devices like ITER is to rely on long plasma pulses with high auxiliary heating. The goal is to inject most of the available power while ensuring the Plasma Facing Components (PFC) safety by limiting the power load just below their operational limits. To measure and monitor the heating of the PFC during plasma operation, the most efficient way is to collect surface temperature information by using a network of infrared video cameras. Then a feedback control based on infrared image analysis is used to control the heat loads in real-time. The image analysis part of the Tore Supra's feedback control consists in detecting high increase of the IR luminance signal beyond fixed temperature thresholds for a set of predefined Regions of Interest (ROI) (see figure 1). It has been successfully applied to the detection of some thermal events [1], as electric arcing. These arcs are caused by a potential difference between the two lateral shields of a heating antenna and can lead to the destruction of sensitive parts like the copper grills of the heating antennas (see figure 2). However, this system has several drawbacks and limitations:

1) working with temperature values make the strong assumption that the infrared digital sensors are always well calibrated,
2) it requires an operator for both editing the ROI each time the PFC configuration changes and manually tune the temperature thresholds,
3) thermal events outside of the ROI cannot be detected,
4) the sensitivity to false detection is high: the presence of only one noisy or dead pixel in a ROI with a temperature higher than the detection threshold is enough to raise a false alarm,
5) different thermal events will not be discriminated if they occur in the same ROI.

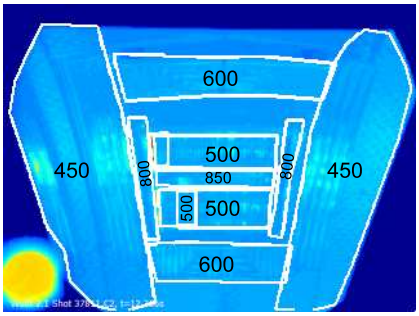


Fig. 1. ROI drawn by the user for the monitoring and the feedback control to prevent from PFC overheating. Temperature thresholds are indicated for each ROI.

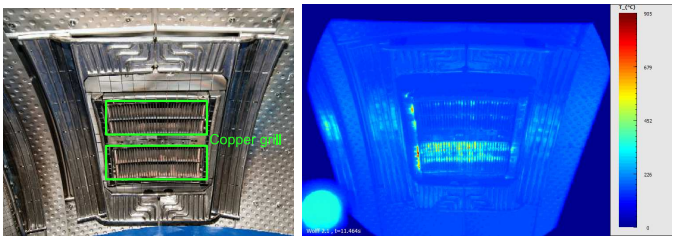


Fig. 2. A heating antenna with the its infrared image during heat load. Electric arcing is visible on the bottom part of the infrared image.

In summary, a need exists in both automation of the processing and better understanding and interpretation of infrared images as, for instance, an accurate identification of new heating zones (hot spots). In this paper, we propose a new approach

for the automatic detection of Thermal Events (TE) inspired from a video understanding framework [2] widely used in videosurveillance applications. The goal is to separate the domain expert knowledge on event modeling from the image processing tasks dedicated to the extraction of low level features from visual data. The major advantage of such a framework compared to the current system is that the *a priori* knowledge of the scene is not inside the image but in the scene model description.

## II. Recognition of Thermal Events

The global dynamic of the infrared image sequences can be classified into two states: steady and transient. During steady state, the average level of the pixel values does not changes or very slowly. Transient states occur when the power injection is increased or modulated. In this case, the pixel variations can be sudden. We call a thermal object a local region in the image which has a high contrast with its neighbourhood. A description of identified critical areas of potential overheat and their related heat source can be found in [3]. Two kinds of thermal objects can be detected in the infrared images: normal and abnormal. Usually normal thermal object dynamics evolve with respect to the heat load whereas abnormal ones have a thermal intensity which can unexpectedly increase, especially during steady states.

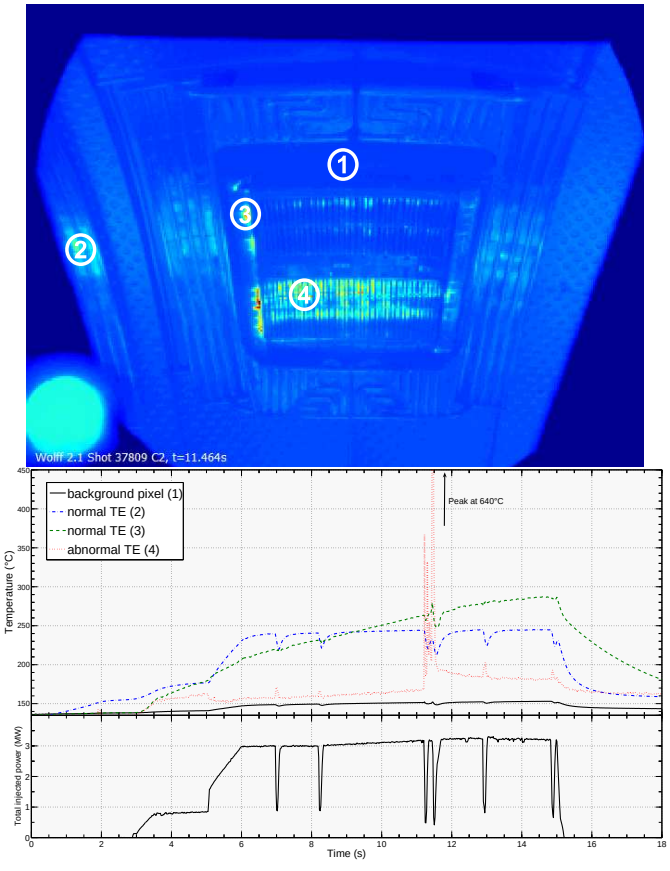


Fig. 3. Temporal evolution of 5 local areas (picked from the infrared frame on top) and of the heating power injection (bottom plot).

Four representatives thermographic behaviours of specific patterns during a pulse are shown in figure 3 and describes below:

(1) background pixels: the temporal evolution is practically null,
(2) reflection area from metallic component (normal TE),
(3) hot spot: this is a normal thermal event caused by the interaction of fast electrons with the PFC (guard limiter). The temperature increases linearly in the time,
(4) electric arcing: strong temperature peaks during the steady state (abnormal TE).

The major difficulty is to be able to efficiently detect such thermal events in a dynamic experimental context with a low false alarm rate. To this end, we follow a process chain as illutrated in figure 4 where each of the three main vision tasks is guided by the domain expert knowledge.

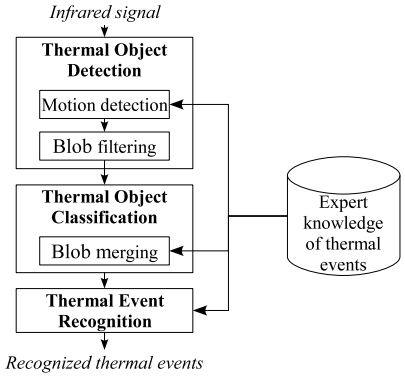


Fig. 4. Process chain of the proposed approach.

### A. *a priori* knowledge formalization

More precisely, we use a formalized visual description of the thermal events to detect. This description relies on a visual concept ontology composed of generic spatiotemporal attributes such as geometric and temporal cues [4]. The main advantage in using such a symbolic description is its reusability for other thermal events to recognize. Indeed, visual concepts are an intermediate level that helps mapping low-level numerical values to a domain class description. For the arcing event, the description used is described in figure 5.

The local contrast of a region $r$ is defined as the ratio $\frac{|\mu_r - \mu_{nr}|}{(\mu_r + \mu_{nr})}$ where $\mu_r$ is the mean value of the pixels in region $r$ and $\mu_{nr}$ the mean value of the pixels surrounding the region $r$. The $\Delta T$ velocity is the positive variation of the temperature $\Delta T = T_i - T_{i-1}$ between the time interval $\Delta t = t_i - t_{i-1}$.

### B. Thermal object detection

Motion is a particularly important cue for object detection in image sequences. Indeed, a moving object is often referred as an object of interest and can then be classified as foreground. The simplest approach to detect moving pixel in image sequences consist in subtracting the current frame from a reference frame. Since background is rarely stationary,

**Domain Class** Electrical arcing **SuperClass** Abnormal Thermal Event

| | | |
|---|---|---|
| **Spatial Attributes** | | |
| Length | [ 50 | 110 ] |
| Height | [ 7 | 20 ] |
| Elongation | [ 2.5 | 16 ] |
| Area | [ 120 | 2200 ] |
| **Temporal Attributes** | | |
| Duration | [ 1 | 8 ] |
| $\Delta T$ velocity | [ 154 | 347 ] |
| **Temperature Attributes** | | |
| Local contrast | [ 1.3e-4 | 0.17 ] |
| Entropy | [ 3.8 | 9.02 ] |

Fig. 5. High-level description of an electric arc. Spatial attributes have been translated from physical values to pixel values. Temporal attributes Duration have been translated from seconds to frames. Ranges values corresponds to observed min and max.

the key issue for any background subtraction algorithm is to efficiently model the background and update it according to the pixel variations. Many approaches have been proposed to background modeling based on unimodal distribution, mixture of gaussians or compressed models (see [5] for an overview). Here the method of Butler et al. [6] is used. The basic idea of this method is to represent each pixel in the frame by a group of clusters. The clusters are sorted in order of the likelihood that they model the background and are adapted to deal with background changes. The algorithm depends on three main free parameters: the number of clusters, the adaptation rate, and the foreground classification threshold. The adaptation rate is directly linked up to the duration and the thermal evolution of the thermal event to detect. A small rate will be adapted to the detection of slow thermal events whereas a high rate will be adapted to the detection of rapid themal events such as electric arcing. Therefore the setting of this parameter depends directly on the *a priori* knowledge given by the experts. In the same way, the foreground classification threshold can be connected to the temperature attributes. Basically, the parameter is set according to the local contrast attribute of the thermal event. Concerning the number of clusters, we observed only small detection differences while varying the value (between 2 and 5), so we decided to set it to 3 in order to maintain a good trade-off between sensitivity and frame rate.

Electrical arcs are oriented horizontally (in the video camera referential) with a strong infrared signature at the copper grill level. Nevertheless, it is very rare to observe the entire pattern in the infrared images. Most of the time, only a collection of pattern subparts are visible and detected in the form of several blobs by the segmentation algorithm. This is why a specific merging process is necessary to reconstruct the whole arcing pattern.

### C. Thermal object classification

According to the symbols used in figure 6, we have defined a blob merging criterion as follows:

$$HVC = \{|y_{O_i}| < |y_{I_i}|, \forall i = 1, 2\} \quad (1)$$

This criterion favor the merge of blobs having the same orientation (here horizontal for the arcs) and capable of *seeing*

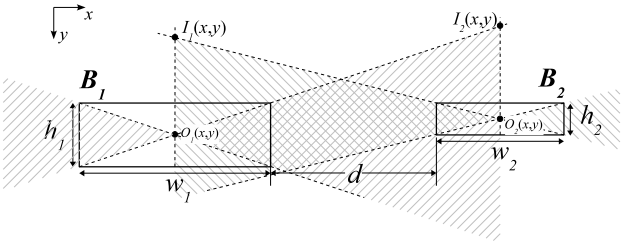


Fig. 6. Blobs features $(w, h, o)$ and inter-blob features $(d, I)$ used by the merging criteria.

each other in this orientation. Two blobs $B_1$ and $B_2$ are defined as visible for each other if the center of $B_1$ (resp. $B_2$) is inside the hatched zone formed by $B_2$ (resp. $B_1$) as seen in figure 6. The visibility is proportional to the inverse of the distance, to the sizes, and to the horizontal elongations of the two blobs (parameters $d$, $w$, and $h$). This criterion prevents from merging distant small blobs. Then, a new bounding box including the two merged blobs is computed and the merging process is repeated until no more merges are possible.

### D. Thermal event recognition

Once each blob has been classified, the last task is to recognize the event patterns from the detected thermal objects. To this end, we also rely on the *a priori* knowledge of figure 5. For the specific case of electric arcing, we use three criteria for the event recognition: the size of the pattern, its shape (i.e. horizontal rectangle), and its duration. This step is essential for the precise spatial localization of the event patterns.

## III. Experimental results

To assess the performance of our system, we have compared the results of the arcing event detection with ground truth data obtained from manual annotations of a pulse dataset. The pulse dataset used for this evaluation is composed of 50 infrared films taken from two heating antennas (the two lower hybrid current drive launchers). A total of 183 arcing events have been annotated. The videos are acquired at 50 frames per seconds. The frame size is 320×240 pixels. A pulse durati1on is between 5 and 62 seconds. This corresponds to a total plasma time of 1496 seconds. Counting results are reported in table I. The frame rate of the C++ sofware implementation is about 23 frames per second.

| Antenna | no. of pulses | GT | no. of detected arcing events | | |
|---|---|---|---|---|---|
| | | | TP | FN | FP |
| C2 | 28 | 138 | 135 | 3 | 4 |
| C3 | 22 | 45 | 41 | 4 | 3 |
| C2 + C3 | 50 | 183 | 176 | 7 | 7 |

TABLE I
Detection results for the arcing event with ground truth (GT), true positive (TP), false negative (FN), and false positive (FP) counts.

Figure 7 presents visual results at each step of the system and for four representative cases. False negative and positives

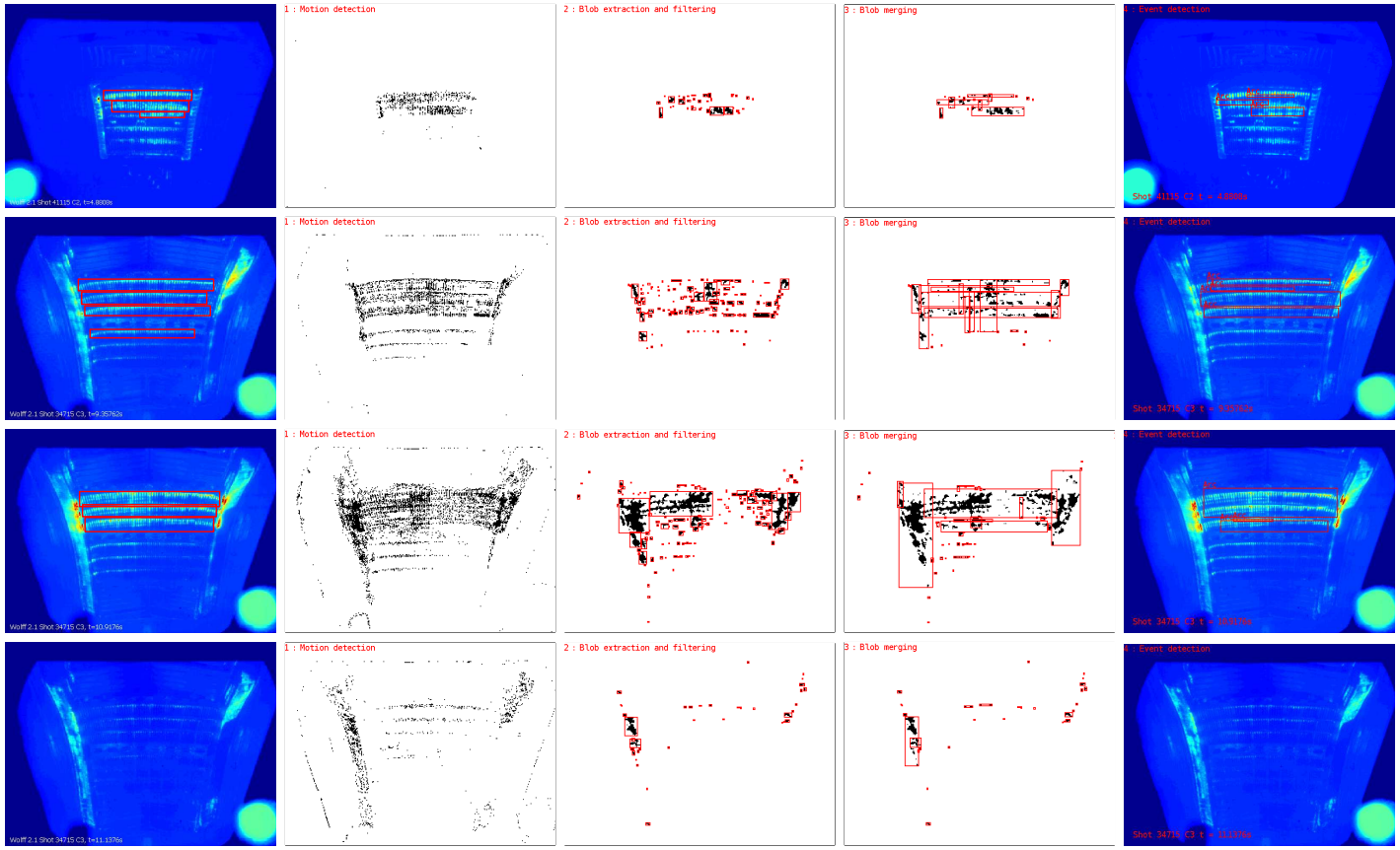


Fig. 7. system outputs after (a) ground truthm (b) motion detection, foreground pixels are in black, (c) median filtering and blob extraction, (d) blob merging, and (e) arcing event recognition with corresponding bounding box superimposed on original image.

results can be explained by the lack of precision of some annotations (ground truth errors), and by the detection errors during the transient states. A simple triggering of the detection algorithm during the transient states should be enough to prevent from such false detections.

## IV. Conclusion and future work

We have proposed a vision-based system for the automatic recognition of thermal events in infrared images of PFC in Tokamaks. The proposed system overcomes the weaknesses of the current thermal event detection system used at Tore Supra by more precise localization and characterization of each TE while using a minimum of explicit knowledge (visual descriptions with corresponding attributes) and basic image processings. If this system has been applied to only one critical TE, it can be easily extented to the recognition of others TE. To this end, we may take advantage of fusion massive databases [7] for the automatic selection and learning of TE attributes by means of data mining techniques. Another way to improve the system performance is to take into account the uncertainty on the algorithm outputs in the system decisions.

The ultimate goal of this system is to improve the reliability of the current real-time control acting on the heating sources. To reach real-time constraints, we plan to implement the thermal object detection algorithm on a FPGA . Finally, such a system could be a solution for the ITER project where wide angle video cameras are planned for the PFC monitoring.

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