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ABSTRACT.

In modern tokamaks visible and infrared video cameras are becoming more and more important to monitor plasma evolution during fusion experiments. Analyzing these images in real-time can provide relevant information for controlling the plasma and the safety of the machines. The realtime image processing capability of Cellular Nonlinear Network based chip has been applied to several tasks both at the Frascati Tokamak Upgrade and the Joint European Torus.

1. INTRODUCTION

In the last years video cameras have been extensively used in magnetic confinement fusion experiments for both the understanding of the physics and the safety of the operation. Both visible and InfraRed (IR) images can be used not only to monitor the evolution of a plasma discharge but also to evaluate specific parameters, from the determination of impurity radiation to the distribution of power loads on the plasma facing components. Data analysis is normally performed off-line, due to the high amount of information to be processed, making the data acquired by the camera quantitatively useful only for post pulse evaluations. The main difficulty in using visible or infrared images for plasma feedback control is the fact that real-time image processing is challenging and heavy in terms of processing time, especially when complex tasks are required. Since digital image processing operates sequentially, it requires high clock frequencies to achieve acceptable performance for real time applications with the consequent problems of consumption, signal integrity and so on. In order to overcome these issues the route of parallel processing has been investigate in Joint European Torus (JET) and Frascati Tokamak Upgrade (FTU) using the approach of analog and mixed-mode circuits, like Cellular Neural/Nonlinear Networks (CNNs) [1] since they are particularly suited for fast computation. The CNNs are an array of simple, identical, locally interconnected nonlinear dynamic circuits called cells. Each cell interacts, via weighted connections, with the cells in the neighborhood of a limited radius. The analog implementation permits parallel processing at the hardware level of the individual pixels. Moreover, the CNN-Universal Machine paradigm [2] provides the capability to program and sequence in time the computational operations. In addition, it permits the storage of the intermediate results and can be implemented as a mixed-signal VLSI chip [3].

Several application of CNN-based hardware and software techniques were developed in the last years at FTU and JET, exploiting both the output of visible and infrared cameras. An overview of these algorithms is here reported together with a brief description of CNNs. The first application was to MARFE detection at FTU exploiting visible images in order to prevent disruptions due to excessive radiation emission. IR images were used at JET to determine the position of the strike-points to complement the measurements of the magnetic coils and to the early detection of hot spot, those points in the wall where the temperature approaches dangerous values.

All these tasks were tested on the ACE16K CNN-based chip [4], a VLSI implementation of the CNN-UM paradigm. The chip is able to process in a parallel way up to 16384 pixels, corresponding to a 128×128 image and to perform a linear convolution of 3X3 neighborhood on them in less than 3μs.

2. CELLULAR NEURAL/NONLINEAR NETWORKS

The concept of CNNs was introduced in 1988 by L.O. Chua [1]. The architecture of the CNN is made up of a basic circuit called cell, containing linear and nonlinear circuit elements (see Fig.1).

Each cell in a CNN is connected to its local neighboring cells, so a direct interaction occurs only among adjacent cells. An example of a two-dimensional CNN is shown in Fig. 2.

The neighborhood of the cell on the i-th row and j-th column, denoted by C(i, j), has the following definition:

$$N_r(i, j) = \{C(k, l) \mid max\ \{\{|k-i|,|l-j|\ \} \leq r,\}\ 1 \leq k \leq M\ ; \quad 1 \leq l \leq N \tag{1}$$

where r is a positive integer number, which fixes the dimension of the neighborhood.

A CNN is entirely characterized by a set of nonlinear differential equations associated with the cells in the circuit. Several mathematical model for the state equation of the single cell has been proposed since their introduction. The model as implemented in the CNN Universal chip family [3], also called Full Signal Range (FSR), is given by the following set of relations:

$$\begin{aligned} C_x \frac{dx_{ij}(t)}{dt} = -\frac{1}{R_x} g\left(x_{ij}(t)\right) + \sum_{C(k,l) \in N_r(i,j)} A(i, j; k, l)\, y_{kl}(t) + \\ + \sum_{C(k,l) \in N_r(i,j)} B(i, j; k, l)\, u_{kl}(t) + I \end{aligned} \tag{2}$$

and the output equation is:

$$y_{ij}(t) = x_{ij}(t) \tag{3}$$

where *u*, *x*, and *y* denote the input, state, and output of the cell, respectively; *Rx* and *Cx* are the values of the linear resistor and linear capacitor, that determine the time constant of the circuit; *A(i, j; k, l)* and *B(i, j; k, l)* are the feedback and control templates respectively; *I* is the bias term, that is constant for all the CNN cells; *g(x)* is the nonlinear function in the state equation (2), depicted in Fig. 3. The templates are matrixes that contribute to implement the analysis algorithm (as discussed further on).

This last element is the main difference between the classical Chua-Yang CNN model [1] and the FSR model. In fact, in the former one, the nonlinearity enters into the output equation and is the integral of g(x). In [3] it has been demonstrated that the two mathematical models are equivalent.

One of the main applications of CNNs is image processing. In this case the input image is mapped on the CNN in such a way that each image pixel is associated with the input or initial state of a particular cell. The CNN evolution implies a transformation of the input image into the corresponding output image obtained directly by the equation (2). In this contest, the template operators work like the instructions in a programming code. A huge amount of templates and template algorithms for a variety of tasks is already available in the literature [6].

The hardware prototype system used in this application is based on two fundamental parts: the CNN Universal Chip prototype, which is a 128x128 CNN chip [4], and the CNN Chip Prototyping and Development System (CCPS) platform [5]. The chip is mixed signal and is developed following the concept of Single Instruction Multiple Data (SIMD)

architectures. It is named ACE16K, where ACE is the acronym of Analogic Cellular Engine to underline the mixed signal nature of the chip (analogue and logic) and the fact it is composed of 16K cells.

ACE16K can be described basically as an array of 128×128 identical, locally interacting, analog processing units designed for high speed image processing tasks requiring moderate accuracy (around 8bits). The system contains a set of on-chip peripheral circuitries that, on one hand, allow a completely digital interface with the host, and on the other provide high algorithmic capability by means of conventional programming memories where the algorithms are stored.

Although ACE16K is essentially an analog processor (computation is carried out in the analog domain), it can be operated in a fully digital environment. For this purpose, the prototype incorporates a bank of Digital-to-Analog (for input) and Analog-to-Digital (for output) converters at the images I/O port. ACE16K is conceived for use in two alternative ways. First, in applications where the images to be processed are directly acquired by the optical input module of the chip, and secondly, as a conventional image co-processor working in parallel with a digital hosting system that provides and receives the images in electrical form. The second mode of operation is the one adopted to obtain the results presented in this paper.

3. CNNS FOR MARFE DETECTION AT FTU

The first application of CNNs to plasma fusion field was MARFE detection at FTU [7]. The MARFE [8] is a radiation instability which appears in tokamaks as a toroidally symmetric ring of enhanced radiation. It usually occurs on the inner side of the torus. The plasma is locally cooled by radiation leading to a self sustained process in which the decrease in temperature enhances radiation losses and further cooling. The effect is due to line radiation from impurities that increases with decreasing temperature.

This instability appears at high density and near the Greenwald limit [9]. After the onset of a MARFE further gas puffing does not lead to an increase of the electron density; moreover strong gas puffing into the discharge with a MARFE leads to a detached plasma or to a hard disruption. In the first case it can be asserted that MARFEs represents a limit to the maximum attainable density but the second one, i.e. the disruption, is a dramatic event in which the plasma confinement is suddenly destroyed. In few milliseconds the current goes to zero and this leads to a large mechanical stress and to intense heat loads. As a consequence it appears that real time control of MARFEs would be a useful mean to extend the plasma operation parameters and to avoid dangerous disruptions. Camera observations of a wide poloidal portion of the plasma edge represent a good candidate for early detection of the MARFE onset and the development of a feedback control in order to mitigate its effects. The idea is, once detected a MARFE in the tokamak, to stop immediately the gas puffing and then to move the plasma column in order to modify, in that region, thermal conduction both parallel and perpendicular to the magnetic field. In this way control of the growth rate of MARFEs should be obtained at least to avoid disruptions.

A preliminary work has been dedicated to translate the physical information about the MARFE in visual features detectable in the images captured by the video monitoring system. The set of visual parameters which has been considered to be representative of the MARFE formation and its speed displacement are brightness, shape and velocity of its growing (see Fig. 4). A further analysis phase revealed that the shape of the MARFE is that of a very stretched ellipse, oriented in a diagonal direction.

These last two visual features obviously depend on the position and tilt of the camera, but they can be considered invariant in this application, since the camera is installed with a fixed position and orientation.

An algorithm has been devised in order to monitor this visual parameters. A threshold is performed to detect the pixel exceeding a given brightness. At this point, a DIAG1LIU [6] template is applied for detecting diagonal lines laying in the SW-NE direction. This operation performs a control on the shape of the black object which, in this case, is an ellipse oriented along a diagonal (SW-NE) direction. Once identified the object shape and orientation, the following step is to perform a check on its growing speed. This can be achieved observing the difference between two consecutive frames, that provides information about the dynamic evolution of the phenomenon. The number of pixels in the difference is evaluated, and in the case it exceeds a given threshold size, a warning message is shown. A detailed description of the algorithm is reported in [9].

The whole algorithm has been implemented on the CNN based chip ACE16K, available in the laboratories of the DIEES-University of Catania. Many videos were analyzed to carry out an algorithm with a high robustness respect to variations on the camera tilt.

The results obtained are shown in Fig.5 where an elaboration of two consecutive frames is presented. It is possible to observe that a MARFE is detected and a warning message “Alert” appears, as can be appreciated in the upper right corner of this figure. During the processing, from this moment on, the warning message will be held on the screen, if the MARFE moves or increases. The video monitoring system installed at FTU and used in this work operates at a temporal resolution of 25 frames/s which is doubled removing the field interlacing providing, in this way, a frame every 20ms [12]. The time, instead, to process two consecutive frames is about 16 ms, which is below the interframe rate. This real time detection system can help in carrying out a safe termination of the experiment when the probability of the occurrence of a disruption is high, thus preventing the tokamak from mechanical and thermal stresses.

4. CNNS FOR STRIKE POINTS DETECTION

In Tokamak plasmas, the divertor is the region of the vacuum vessel explicitly designed to handle power losses. In JET history several topological solutions have been tested as far as the divertor is concerned.

The one used for the discharges, whose results are here described, is shown schematically in Fig.6. The typical Xpoint plasma configuration is also shown: it is characterized by the existence of a separatrix and a scrape-off layer. The former is the last closed flux surface that separates the closed magnetic field lines from the open ones which strike the vacuum vessel, while the latter is the region of the plasma where the magnetic field lines intersect wall elements, in this case the divertor. The plasma power losses are deposited along this region. The intersection of the separatrix with the divertor target plate represents a strike point.

In JET the position of the strike points is mainly derived from magnetic measurements executed through loops and pick-up coils located around the vacuum vessel. These measurements, performed at some distance from the plasma, can be extrapolated across the current-free region to identify the last closed flux surface. The code used at JET to determine the plasma shape and therefore also the position of the strike points is XLOC [13]. The main output of XLOC consists of the definition of the last closed flux surface, also called separatrix.

In JET divertor various thermocouples are also located in the divertor tiles, covering the whole region were the magnetic field lines can intersect material surfaces (see Fig.6). The region of maximum thermal load, which can be considered as the position of the strike points, can be identified thanks to the thermocouple signals.

Another very useful diagnostic to derive information about the power deposition in the JET divertor is represented by infrared imaging. At the time of the experiments, two IR cameras framing the divertor region were available at JET. They measured the infrared radiation in the interval 3-5μm with a resolution of 128×128 pixels [14]. One camera sees the outer leg of the divertor, the other the inner leg and, as far as real time control is concerned, the two views can be considered representative of the entire divertor, given the toroidal symmetry of the machine.

Also in this case, a preliminary analysis was necessary to determine how the presence of the strike points reflects itself in the visual features of the camera images. The strike points, indeed, can also be considered the region of maximum thermal load on the divertor tiles that is translated in an infrared image as the region of maximum brightness. A first manual analysis of images from JET IR cameras proved that the shape of the strike points consists of two thin bands of high emission in the whole divertor region, oriented in the toroidal direction.

A specific procedure was developed to derive the position of the strike points from the data of the infrared cameras exploiting the capabilities of CNN technology. The images of the two divertor legs have in general different brightness, related to the different temperature the strike points reach in the two regions of the divertor. So it is necessary to perform an independent processing procedure for each one of them.

A detailed description of the procedure is given in [11]. It is capable of supplying the position of both the inner and the outer strike points within 20ms. In particular, the time to identify the strike points in the image is comprised between 13 and 19 ms, depending on the brightness condition of the starting frame (see Table I).

This time resolution is acceptable for the vast majority of JET applications. It is indeed necessary to consider that in general the thermal effects, which can affect the tile temperature and change infrared emission, do not change much on shorter time scales.

In order to assess the accuracy of the proposed approach, a systematic comparison with the results of XLOC and the thermocouples measurement was undertaken (see Fig. 7 and 8). To this end the co-ordinates of the strike points obtained with the CNN were compared with the ones given by XLOC for the intersection of the separatrix with the divertor and with the position of maximum load as given by the thermocouples. A good congruity between CNN and XLOC calculated strike points is noticed.

The fact that CNN detects the maximum power load which is not always coincident with the intersection of the separatrix with the divertor is confirmed by the comparison with the thermocouples. Indeed, the positions of the CNN calculated strike points are close to the position of the thermocouples presenting the maximum temperature. In Fig.8, for instance, the position of the CNN calculated strike point is near the 7U thermocouple and then shifts to the 7L once the temperature measured by this thermocouple registers a steep rise.

5. CNNS FOR HOT SPOT DETECTION

Another application of IR imaging and CNN-based image processing is the early detection of hot-spots [15]. One of the future ITER relevant enhancements at JET will be the installation of a Beryllium wall. Since Be is much more vulnerable than stainless steel (the present JET's wall material) preserving the integrity of the plasma facing components will be one of the main issues in future JET experiments. Detecting on time the presence of hot spots, i.e. regions of the first wall where the temperature approaches dangerous levels, is considered crucial in the safety strategy as they are considered naturally the points more prone to significant damage. CNN technology was applied to the real time identification of hot spots.

Analyzing the data from JET cameras [16] it is possible to identify three main sources of anomalously high emission in the infrared region of the spectrum in JET (see Fig. 9).

Some parts of the vacuum vessel, like the limiters or the target plates, can reach very high temperatures, because they are the region were most of the plasma wall interactions take place in normal conditions. These locations will have to be monitored continuously once JET new wall is installed to both understand the behavior of the materials and to guarantee safe operation of the device. On the other hand, these regions are designed to withstand high energy fluxes and therefore specific thresholds will have to be used for them. Moreover their position and shape are fixed and therefore their monitoring relatively straightforward.

A different emission is produced when other parts of the first wall, not meant to absorb a lot of energy, are subject to strong heating in case of unforeseen events, like disruptions, ELMs or errors in the set up of the magnetic configuration. The shape of these hot spots can be very different and their location inside the viewing cone of the camera quite unpredictable. Moreover their position can change during the discharge. Particularly during fast events like ELMs and disruptions, a third type of IR emission can be due to particles ejected from the first wall and entering into the plasma.

If they are big enough not to be immediately vaporized, struck by the plasma they can reach high temperatures and be clearly detected in the IR images. They have normally relatively small dimensions and fast changing position inside the field of view.

Taking into account the different nature of these IR emissions, two different types of algorithms for the identification of the hot spots were developed. The first one, for the so called static detection, performs the analysis of a single frame at the time. It is more suited to the monitoring of the fixed parts of the machines, like the plasma facing components (limiters and divertor). A second approach, called dynamic detection, is based on the difference between subsequent frames. The latter algorithms are more complicated but they allow to follow the growth of the hot spots and their movements inside the field of view. A detailed description of both the algorithm is reported in [15].

Both algorithms were tested using frames acquired by JET new wide angle infrared camera. As parts of the image are not relevant to the end of detecting hot spots (because they include regions of the vessel not in contact with the plasma), the frame was cropped before processing it in order to speed it up. The processed image is so reduced to a 384×384, eliminating also the portion of the frame, which sees the divertor as there is already another infrared camera (KL3) that monitors this part of the machine with greater accuracy.

An example of the result produced by the static algorithm is reported in Fig.10. The contour of the detected regions is superimposed to the starting frame. It is possible to observe that they represent the point of maximum brightness assimilable, at this step, to the hottest point in the vessel.

The execution times for both the algorithms are reported in Table II. The execution time is in the order of 100ms to process the whole 384×384 frame. The time required to process only a 128×128 subframe is about of 20ms. This higher time resolution could be very helpful for machine protection. For instance, particularly delicate parts of the machine, like the RF antennas, which occupy a region of the image not wider than two 128×128 images, could be monitored with a higher time resolution.

CONCLUSIONS

The visible and infrared emission contains a lot of useful information exploitable for plasma monitoring to enhance the performance or the safety of the tokamak experiments. The data provided by visible and infrared camera installed at FTU and JET were processed in order to monitor dangerous plasma phenomena, like MARFE or hot spots, or to extract relevant parameter like the maximum thermal load position in the divertor. To take advantage of the potentialities of CNNs, several algorithms were devised to perform the previously mentioned tasks. Thanks to the capabilities of ACE16K, a VLSI implementation of CNNs, the processing time for the various tasks is below the inter-frame rate.

The algorithms here reported represent the first application of CNNs to fusion experiments. Further investigation is going to be performed in order to assess the potential of CNN technology for real time applications in the environment of reactor class tokamaks.

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TABLE I.

Execution time for strike point detection algorithm

OPERATION	**TIME (ms)**
Inner strike detection	7 - 10 ms
Outer strike detection	6 - 9 ms
TOTAL	**13 - 19 ms**

TABLE II.

Execution times for the static and dynamic algorithm applied to a full frame or a 128×128 subframe.

ALGORITHM	**TIME (ms)**
Static Detection (full frame)	~ 110 ms
Dynamic Detection (full frame)	~ 100 ms
Static Detection (128×128)	~ 19-20 ms
Dynamic Detection (128×128)	~ 20-21 ms

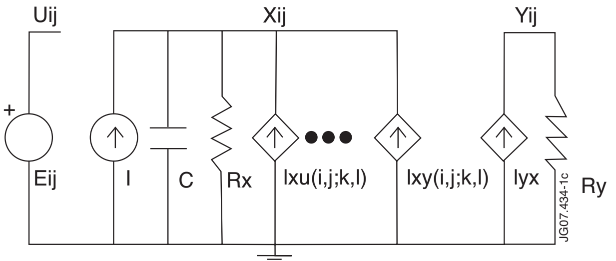

Figure 1: The Chua-Yang cell circuit model

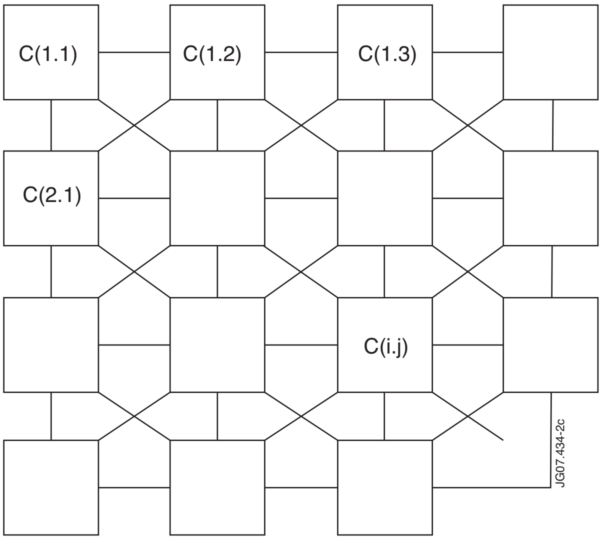

Figure 2: An example of a two dimensional CNN

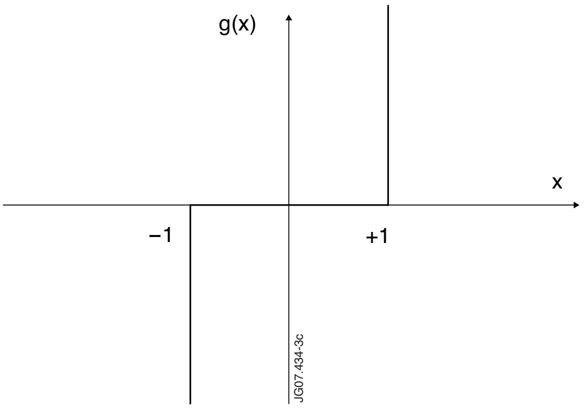

Figure 3: Nonlinear function in the Full Signal Range CNN model, as implemented in the CNN chip

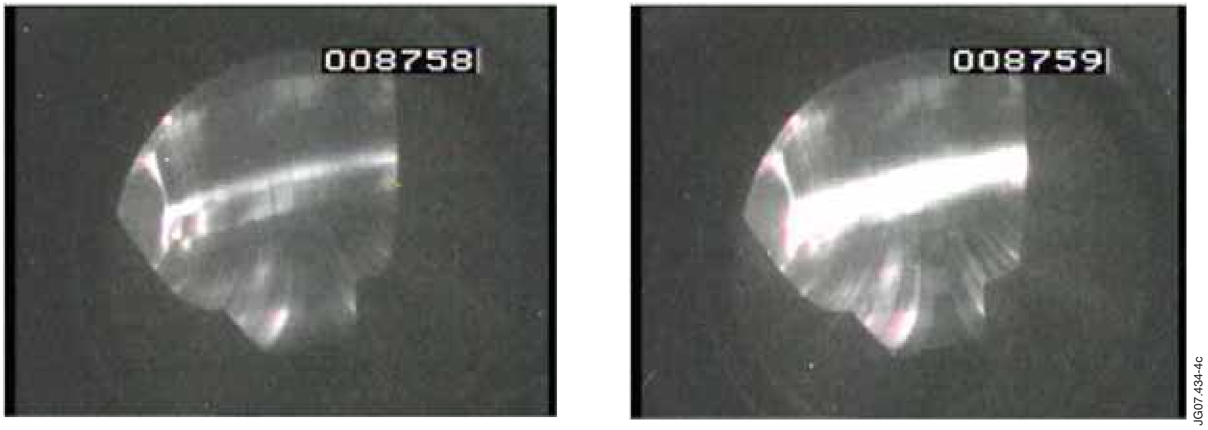

Figure4: Example of MARFE growing from FTU Pulse No: 22214

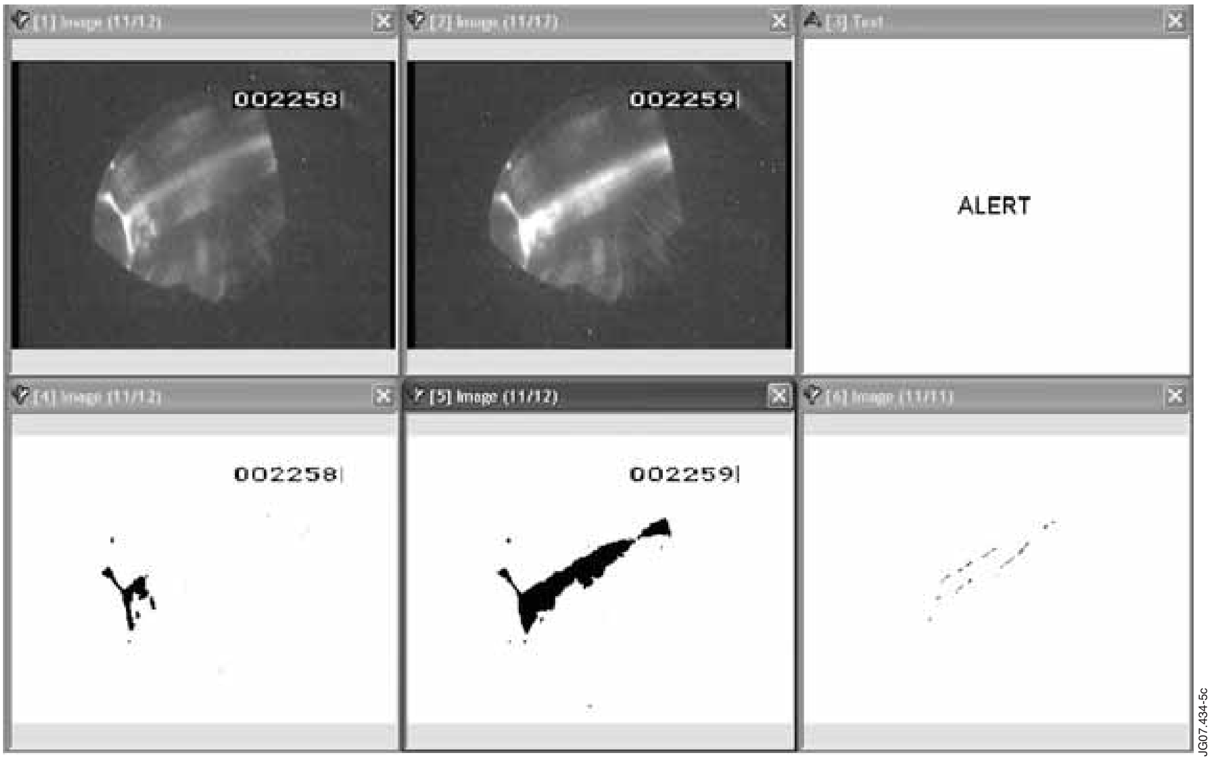

Figure5: An elaboration of two consecutive frame. It is possible to observe in the upper-right frame the message ALERT caused by a MARFE, whose shape can be noticed in the lower frames [9].

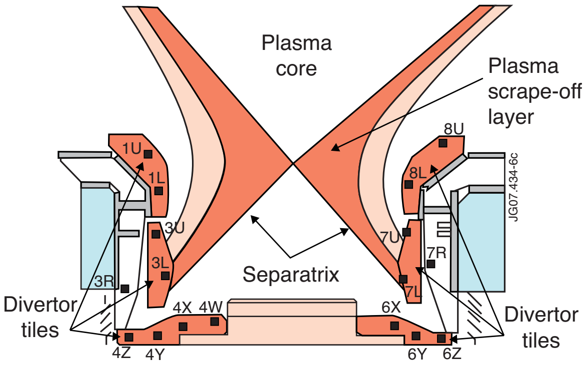

Figure 6: A schematic outline of JET divertor topology. The dark squares represent the position of the thermocouples.

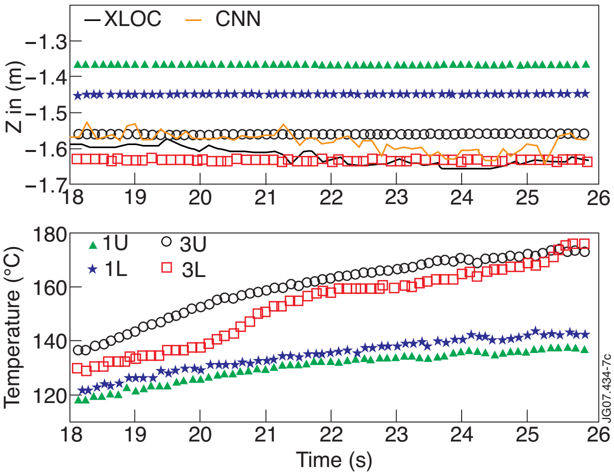

Figure 7: In the top figure, the time evolution of the CNN and XLOC calculated strike points is shown, together with the position of the corresponding thermocouple for the coordinate Z in the inner leg of the divertor. In the bottom figure, the time evolution of the thermocouples temperature is shown (Pulse No: 62216) [11].

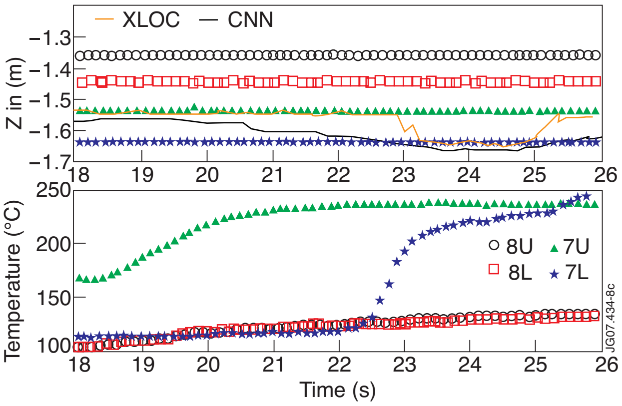

Figure 8: In the top figure, the time evolution of the CNN and XLOC calculated strike points is shown, together with the position of the corresponding thermocouple for the coordinate Z in the outer leg of the divertor. In the bottom figure, the time evolution of the thermocouple temperature is shown (Pulse No: 62216) [11] .

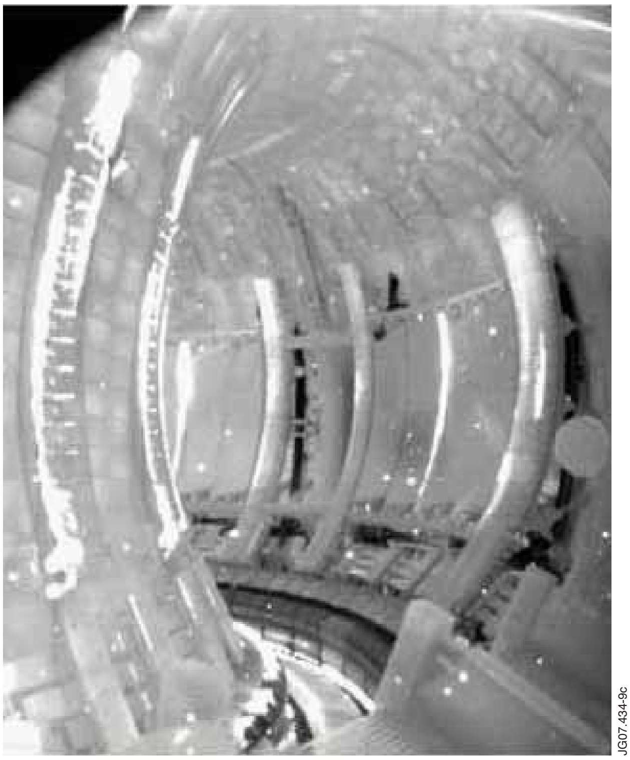

Figure 9 Example of the three main types of hot spots as seen with JET wide angle IR camera. (Pulse No: 66503). The smallest circular bright spots are particles entering the plasma. The big crescent shape bright regions are on the limiters, locations designed to withstand high powers. Some smaller bright spots on the top are due to plasma wall interactions changing fast with time.

Figure 10: Example of static detection of hot spots. The contour of the detected regions is reported superimposed to the starting frame.