EFDA–JET–PR(10)03

A. Murari, J. Vega, T. Craciunescu, S. Gonzalez, S. Palazzo, G. Vagliasindi,
D. Mazon, M. Gelfusa, J. F. Delmond, A. de Maack
and JET EFDA contributors

Latest Developments in Image Processing Methods and Technologies for Magnetic Confinement Nuclear Fusion

Latest Developments in Image Processing Methods and Technologies for Magnetic Confinement Nuclear Fusion

A. Murari[1], J. Vega[2], T. Craciunescu[3], S. Gonzalez[2], S. Palazzo[4], G. Vagliasindi[4], D. Mazon[5], M. Gelfusa[6], J. F. Delmond[7], A. de Maack
and JET EFDA contributors*

JET-EFDA, Culham Science Centre, OX14 3DB, Abingdon, UK

[1]Associazione EURATOM-ENEA sulla Fusione, Consorzio RFX Padova, Italy
[2]Asociación EURATOM/CIEMAT para Fusión. Avda. Complutense, 22. 28040 Madrid, Spain
[3]EURATOM-MEdC Association, National Institute for Laser, Plasma and Radiation Physics, Bucharest, Romania
[4]Dipartimento di Ingegneria Elettrica Elettronica e dei Sistemi-Università degli Studi di Catania, 95125 Catania, Italy
[5]Association EURATOM-CEA, 13108 St Paul-lez-Durance, France
[6]Associazione EURATOM-ENEA - University of Rome "Tor Vergata" , Roma, Italy
[7]Arts et Métiers ParisTech Engineering College (ENSAM) 75013 Paris
[8]École des Ponts ParisTech 6-8 avenue Blaise Pascal Cité Descartes-Champs-sur-Marne 77455 Marne-la-Vallée cedex 2
** See annex of F. Romanelli et al, "Overview of JET Results",*
(Proc. 22 nd IAEA Fusion Energy Conference, Geneva, Switzerland (2008)).

Preprint of Paper to be submitted for publication in
IEEE Transactions on Intelligent Systems

ABSTRACT

Video cameras have recently become common diagnostic tools in Magnetic Confinement Nuclear Fusion. They provide essential information for both the control of the experiments and the physical interpretation of the results. Since these cameras can produce up to hundreds of kiloframes per second and their information content can be very different, depending on the experimental conditions, several new image processing tools had to be devised to fully exploit these diagnostics. New structural pattern recognition algorithms have been developed to retrieve the required information from the large reservoirs of video frames in an efficient and reliable way. Specific real time algorithms, based on the computational paradigm of Cellular Nonlinear Networks, have been implemented on FPGAs to identify hot spots on the vacuum vessel and therefore to protect JET plasma facing components. Various machine learning tools, in particular Support Vector Machines, have been given Hu moments as input to automatically identify plasma instabilities. The methodology of the optical flow has allowed deriving information about the movement of objects in 3 dimensional space even if they have been detected by a single camera. A new anomaly detector based on an original interpretation of external support vectors is being tested with very positive results. Many of the more innovative solutions are based on quite general methods and are therefore expected to be applicable also in other fields of research.

1. INTRODUCTION

For human beings visual perception constitutes the main source of information. The part of the brain devoted to image processing is significantly larger than the one of all the other senses. On the other hand, only recently, with the advent of cameras and computers, it has become easy to capture and store images on external supports and not simply on individual memories. Whereas up to the end of the nineteen century only artists and illustrators had the privilege of producing images, typically on some form of paper or canvass, nowadays it has become possible for everybody not only to record individual frames but also entire videos. In particular digital video cameras have improved and advanced so much that they are now found in a variety of devices, including cellular phones, portable digital assistants, hand-held video game consoles and a whole host of other portable devices Video cameras have therefore become a tool of convenience, they are being used regularly to record, create and share information and they are now playing every day a greater role in society, media and culture [1].

The continuous progress in camera technologies has resulted in commercial products with performance that have become very appealing in many scientific applications. In Magnetic Confinement Nuclear Fusion (MCNF), the number of cameras deployed on the various experiments has increased steadily in the last decades. Nowadays they have become routine diagnostics with multiple applications, ranging from protection of the first wall to the analysis of plasma instabilities and even the characterisation of turbulence.

On the other hand, the widespread use of cameras has emphasized the need for advances and

developments in image processing techniques. The main challenges to image processing for MCNF can be grouped into four categories. First of all, the retrieval of the necessary information from the repositories of images has become quite a challenge. JET database for example has become quite large, exceeding 90 Terabytes, of which at least half is made of videos [2]. Some JET cameras can produce hundreds of thousand of frames for a plasma discharge, for a total of Gigabytes of data per shot. Analysing these amounts of data manually has become impossible and therefore new methods of information retrieval, based on structural pattern recognition, have been developed (see section 2) [3].

The second issue is constituted by the need to obtain at least a basic level of information from the videos in real time. This is complicated by the fact that the typology of objects to be detected is very wide and that the general appearance of the frames (from background luminosity to the level of noise) can change dramatically from experiment to experiment. Moreover, since many plasma events have time constants of ms or tens of ms, fast, flexible but at the same time robust algorithms are necessary. Typical serial algorithms, even when optimised, are not adequate because their computational time depends strongly on the content of the images to be analysed. To overcome this difficulty parallel computation is required, which has been achieved at JET by implementing the computational paradigm of Cellular Nonlinear Networks [4] on FPGAs (see section 3). Various machine learning methods have proved also to be indispensable to properly classify the various objects appearing in the frames particularly of the visible cameras (see also section 3).

The third major group of challenges is the need of providing various forms of information for physical studies. A typical requirement is the velocity of objects, instabilities, pellets or others, captured by the cameras. On the other hand, since accessibility for measurement is always problematic in Tokamak devices, stereoscopic vision is rarely an option and therefore the required information must be obtained collecting images from a single point of view. Under appropriate assumptions, the method of the optical flow [5] has proved to be very effective in providing information of objects in the 3D space from the images of individual JET cameras (see section 4).

Another category of challenges for image processing in MCNF is linked to image interpretation and in particular to the need to identify anomalous behaviour in the discharges. A new event detector, based on Support Vector Machines (SVM) [6], has been recently developed at JET and it is being applied to this problem of anomaly detection.

The challenges and difficulties in image processing for MCNF have the positive implication that the margins for innovation are quite substantial, particularly in the perspective of the next generation of devices: the main future prospects of image processing in MCNF are briefly described in the last section of the paper.

With regard to the videos, which have been used to obtain the results shown in this paper, they are obtained by JET most interesting cameras for image processing applications. These are cameras installed on a dedicated endoscope providing a wide-angle view (field of view of 70 degrees) in the infrared range (3.5 to 5μm) and in the visible. The wide angle view of the system includes the main

chamber and the divertor [7]. The diagnostic consists of an endoscope formed by a tube holding the front head mirrors, a Cassegrain telescope, and a relay group of lenses, connected to the camera body. To increase the reactor-relevance of the project, mainly reflective optical components have been installed, since they can better cope with high neutron radiation. In the infrared the global transmission of the endoscope is higher than 60% and the diagnostic is designed to measure from the JET typical operating temperature of 200°C up to a maximum temperature of 2000°C. The diagnostic spatial resolution is diffraction limited and, assuming a 10% error in the measured photon flux, an overall spatial resolution of 2 cm at three meters has been estimated. A frame rate of 100 Hz at full image size (496x560) can be achieved and it can be increased up to 10kHz by reducing the image size to 128x8 pixels, located on any position in the field of view. A typical frame acquired by JET infrared wide angle camera is shown in Figure 1. The fast visible camera located on the same endoscope has a 1024x1024 CMOS pixel detector, which can be acquired full frame up to 3kHz. The maximum frame rate of the camera is 250 kframes/s (for a reduced frame of 128x16 pixels).

2. INFORMATION RETRIEVAL BASED ON PATTERN RECOGNITION

Traditionally computer databases are address based and therefore the location in memory must be known to retrieve the required information. This is different from human memories which are content based, i.e. somehow people manage to retrieve the information on the basis of its content. Content based databases would be very useful in science. In MCNF in particular, the first approach to the data is certainly based on the content of the signals or the images acquired during an experiment and this requires in principle to scan the whole traditional database until the required information content (typically a signal of a specific form) is found. As mentioned, the cameras located on JET wide angle endoscope have the potential to produce terabytes of data per JET discharge (30-40 discharges per day are normally performed). Exhaustive manual searches of hundreds of thousands of frames per discharge or per day are not an option and therefore automatic techniques are required. The first step in data analysis for fusion typically consists of a visual screening of the signals or the images. Since this is a very high level visual process, the methods developed to help the physicists in this respect are based on structural pattern recognition. This approach is based on a concept of similarity between images which is based on the structure of the image and not on involved mathematical concepts, such as correlation or covariance, which are difficult to appreciate intuitively. Indeed the main objective of the proposed method is to help the user during the first screening phase of the data. In more detail, the Haar transform is applied to the images first. Then the coefficients of the transform are grouped in different classes depending on their value. To each of these classes a letter is associated, transforming a matrix of pixels (the original image) into a bidimensional array of letters. The obtained matrix of letters can be codified using a relational database (PostgreSQL for the results presented in this paper) and therefore searched very efficiently. The patterns to be retrieved are bidimensional. The strategy of the search consists of looking for the first rows in the pattern. Once a match for this first row has been found, it is then determined whether also the other rows of the bidimensional pattern coincide.

An example of the results is presented in figure 2, which shows the user interface available to the users. A particular region of interest of a visible camera image, basically the divertor, has been selected (part within the square in the central frame of figure 2) and then the pattern recognition routines manage to identify the frames in the database where the same or a similar pattern is present. For a database of 26000 frames and a total of more than 6 Gigabytes of data, the additional space in memory is less than 0.5% of the original images and is therefore negligible. The search takes a matter of minutes and therefore, even if of course this is orders of magnitudes better than a manual search, parallelisation techniques are being developed to improve this aspect.

3. REAL TIME IMAGE PROCESSING FOR PROTECTION AND CONTROL

3.1. INFRARED THERMOGRAPHY FOR PROTECTION OF THE FIRST WALL

The capability of materials to withstand the power loads induced by thermonuclear plasmas constitutes one of the major issues on the route to a commercially viable nuclear fusion reactor. Therefore a significant part of the scientific and technological efforts on present day Tokamaks is devoted to identifying the best combination of materials capable of withstanding the power and particle loads of high temperature plasmas without spoiling their performance. This problem, very significant for ITER, is already important on JET and will constitute one of the central aspects of both the operation and the scientific activity after the installation of the new Be wall and the W divertor. Since high temperature plasmas do not emit infrared radiation, InfraRed thermography (IR) is a very useful tool to determine the surface temperature of the plasma facing components. For protection and in general for feedback applications, the analysis of the images must be performed in real time.

A series of serial codes, implementing traditional image processing algorithms based on linear algebra, have been developed at JET to identify the hot spots on JET internal surface of the vacuum vessel. Hot spots are regions of the plasma facing components which during a discharge reach temperatures above a certain threshold determined on the basis of machine protection requirements. These traditional algorithms have a very high accuracy and indeed manage to identify the hot regions with practically 100% of success rate. These results have been verified using a database of 11300 frames of JET wide angle IR cameras, which have been all analysed manually by the experts to determine the hot spots. An example of detection of hot spots is given in the bottom picture of figure 1.

The main weakness of this solution is that these serial algorithms present a computational time which depends strongly on the contents of the images. If the number of pixels to be processed increases so does the computational time. This is illustrated in figure 3 in which the frames of a video acquired during a discharge are analysed and the computational time required for each one has been calculated. In general, for the more typical parts of the video, the algorithm manages to process about 55 frames per second but in some special cases, the required time can even exceed 9 seconds. This is not a very satisfactory situation because anomalous frames are the ones that typically indicate that something is not right with the discharge and an urgent decision must be taken.

To overcome this problem, the Cellular Nonlinear Network (CNN) paradigm has been tested [4]. A CNN usually consists of a bidimensional array of cells, the evolution of which is modelled by a nonlinear dynamical system and depends on the current state of the cell and on the states of the cells in its neighbourhood (usually, a 3x3 submatrix surrounding the target pixel). The evolution of the states also depends on a set of values called a template, which consists of two 3x3 matrices – called A, the feedback operator, and B, the input synaptic operator— and a bias constant, z_{ij}. CNN are therefore powerful tools for local image processing, provided the size of the array is equal to the size of the input images and pixel values are mapped on state values. The most commonly used model for image processing is the full-signal range (which means the output of the cell is equal to the state value) space-invariant CNN, whose governing equation for an individual cell becomes:

$$\begin{aligned} \dot{x}_{ij} = -x_{ij} + \sum_{k=-1}^{l} \sum_{l=-1}^{l} a_{kl}\, x_{i+k,\, j+l} + \\ + \sum_{k=-1}^{l} \sum_{l=-1}^{l} b_{kl}\, u_{i+k,\, j+l} + z_{ij} \end{aligned} \tag{1}$$

where the indexes k and l vary on the 3x3 of neighbours of cell C(i,j); x_{ij} is the state of the cell; a_{kl} and b_{kl} are the elements of the feedback and input synaptic operators respectively; u_{kl} is the input of cell C(i,j), that is the grey level value of the pixel in the input image corresponding to target cell. Leaving aside the mathematical details, a CNN can therefore be considered basically a matrix of differential equations modelling the evolution of the state of each matrix cell, each pixel in our case. From an implementation point of view, it is important to notice that the task accomplished by the CNN (i.e., the filter to be applied to the image) is specified by the two 3x3 matrices of coefficients and a constant. Therefore, it is possible to easily vary the kind of filter implemented by the CNN just by modifying these coefficients. In the application described in this paper, the CNN system of equations, which has been implemented on the FPGA, is based on the Falcon architecture [8], which allows for easy parallelization and overlapped execution of subsequent filters. The Falcon architecture consists of an array of processing cores, among which the input image is divided to increase parallelism. So each operation is carried out in parallel by the cores for the various columns of the image whereas each row of cores performs subsequent algorithm iterations.

The results obtained with the implementation of the CNN on the Virtex-4 XC4VSX35 FPGA mounted on an ML402 evaluation board are very positive. The accuracy is extremely good and comparable to the serial algorithm; practically the success rate is 100%. Moreover, the computational time is absolutely deterministic and a speed of 100 frames/s has been achieved with just one column of cores. This frame rate is already completely adequate for hot spot detection at JET but increasing the number of cores to 10 would easily allow performing image processing of kHz frequency.

3.2. IMAGE PROCESSING OF VISIBLE VIDEOS FOR INSTABILITY IDENTIFICATION

The results of the hot spot detection are quite positive but they have been obtained using frames of

JET IR camera. Since high temperature plasmas do not emit in the IR, these images are relatively clean and in any case much less complex than the ones of the visible, which can present a much more involved phenomenology. The videos detecting radiation in the visible can indeed be much more affected by reflections, emission due to plasma instabilities, emissions due to objects, dusts or flakes, dropping into the plasma etc. Also the general level of background luminosity can vary significantly from one experiment to the other. Therefore even a simple thresholding step cannot be performed in the usual simple way. To obtain the results presented in this sub section, the first extraction of the high luminosity pixels has been performed by first blurring the original image. This is achieved by replacing the grey level of each pixel with an average over a suitable area surrounding it. Then the blurred image has been subtracted from the original one and then the thresholding is performed on the difference. This is the only robust way identified to perform even this seemingly simple preprocessing step. One important objective of image processing for visible cameras in JET has been the real time identification of Multifaceted Asymmetric Radiation from the Edge (MARFE) events [9]. These instabilities manifest themselves as ribbons of radiations moving up and down the vacuum vessel on the high field side, as shown in figure 4.

To automatically identify these instabilities a classifier based on Support Vector Machines has been trained. More than 4000 frames have been analyzed manually to provide the training and the test sets (60% and 40% of the frames respectively). Since the objects to be detected change position and rotate during the time evolution of the discharge, the simple barycentres of the ribbon like regions due to the MARFEs are not enough to guarantee a sufficiently high rate of success. To improve the success rate additional information is required, which has been provided as the first two Hu moments. The Hu moments are a combination of central moments of an object in an image, which are practically invariant under rotation, translation and rescaling [10].

Combining the centre of mass of the MARFE with the first two Hu moments as inputs to an SVM classifier has proven to provide the maximum success rate. The kernel of the SVM classifier more suited to this application is the radial basis function. The error rate obtained with this solution is of 1.5% false negatives and 0.97% false positives over the aforementioned database. A pictorial example of a MARFE highlighted by the algorithm with a red contour is shown in figure 5.

4. IMAGE PROCESSING FOR PHYSICAL UNDERSTANDING

The estimation of motion information from image sequences is a recurrent problem in computer vision. In fusion the poor accessibility of the devices makes very difficult the deployment of more than one camera with the same field of view. Therefore stereoscopic methods are not applicable and the optical flow approach has been adopted. The objective of the analysis consists of finding the vector field, which describes how the image is changing with time. Under certain assumptions, this information about the optical flow can be translated into knowledge about the movements of the objects in the 3D space covered by the camera.

The basic assumption of all optical flow techniques is that the emission of objects in subsequent

frames does not change over time, which allows writing:

$$f(x, \Delta x, \Delta y, t + l) - f(x, y, t) = 0 \tag{2}$$

where f is the intensity and Dx and Dy are the two displacements from one frame to the next. For small displacements, the Taylor expansion of equation (3) can be used to reformulate the optical flow constraint as:

$$f_x u + f_x v + f_t = 0 \tag{3}$$

where subscripts denote partial derivatives and u and v are the two components of the optical flow. Unfortunately in practice solving equation (4) is an ill posed problem since small perturbations in the signal can create large fluctuations in its derivatives. A typical method to alleviate this drawback consists of implementing image smoothing techniques which can reduce the effect of noise and stabilize the differentiation process. The smoothing of the image sequence is typically performed prior to differentiation by convolving each frame with a Gaussian function (called K_r in the following). Smoothing can be extended also to the temporal dimension. However, from the mathematical point of view, even after proper smoothing is applied, the problem of finding the flow field solution of equation (4) remains ill-posed and a single equation is not sufficient to uniquely compute the two unknowns (the so-called aperture problem). The most widely used techniques to tackle with this problem are differential methods. They can be classified into local methods such as the Lucas–Kanade technique [11] and into global methods such as the Horn/Schunck approach [12]. Local and global differential methods have complementary advantages and shortcomings. Local methods assume a small neighbourhood of constant flow. For a neighbourhood of size ρ, the optic flow (x,v) can be determined at the location (x,y,t) from a weighted least square fit by minimizing the function:

$$E_{LK}(u, v) = K_\rho * ((f_x u + f_y v + f_t)^2) \tag{4}$$

A sufficiently large smoothing is very successful in rendering the method robust against noise. The problem remains severe in flat regions of the emission, where the image gradient vanishes and, consequently, the aperture problem persists and the method is unable to produce dense flow fields. In order to avoid this drawback, global methods supplement the optical flow constraint with a regularizing smoothness term. The optical flow (u,v) is determined as the minimizer of the global energy functional:

$$E_{HS}(u, v) = \int_\Omega ((f_x u + f_y v + f_t)^2 + \alpha(|\nabla u|^2 + |\nabla v|^2)\, dxdy \tag{5}$$

where $\alpha > 0$ determines the amount of smoothness. Larger values for α result in a stronger

penalization of large flow gradients and lead to smoother flow fields. Unfortunately global methods have been observed to be more sensitive to noise than local differential methods.

Brun et al. [13] noticed the similarity between equation (5) of the Lucas-Kanade method and the first term under the integral in the formulation (6) of the Horn-Schunck method. Based on this observation they succeed to formulate a hybrid Combined Local-Global (CLG) class of methods, which bring together the robustness of local methods with the density flow fields which characterize the global approaches. These methods have been studied and optimized for the very specific case of JET images as described in detail in [14]. A multi-resolution coarse-to-fine procedure was also used in order to cope with large displacements of objects between consecutive frames, characteristic of plasma images captured by JET fast visible camera. The pyramid of multi resolution images is derived from the original frame by successive down-sampling and Gaussian smoothing steps. Optical flow calculation starts at the coarse level, where the displacements are small and consequently the linearization of the grey value constancy assumption is satisfied. This estimate is then refined step by step along the pyramidal structure.

The final results obtained for JET images are quite encouraging. It has for example been possible to estimate the velocity of solid, cryogenic, hydrogen isotope pellets, which are injected in Tokamaks for particle fuelling as well as for instability control (ELM triggering and mitigation). Their importance resides in the fact, among other things, that they open access to operational regimes not reachable by gas puffing. An example of the results is reported in figure 6, where it is shown how the optical flow estimate is very close to the nominal speed of the injected pellets. The optical flow method has been successfully used also for the evaluation of the speed of various plasma instabilities, in particular ELM filaments and MARFEs. As an illustrative example Figure 7 displays the velocity field for the MARFE in Fig.4 (top-right).

It is worth mentioning that the real images provided by JET fast visible camera can be affected by discontinuous movements in the objects, low grey-level in-depth resolution and too slow acquisition rate. Therefore the basic assumptions of the optical flow model may not be always satisfied. Therefore dedicated techniques able to prevent the calculation of an inaccurate velocity have been devised. A procedure for the assessment of the uncertainties of the method has been developed and applied. Extensive tests have also been performed on experimental data to fine tune the parameters of the optical flow model for each of the various applications.

5. A NEW APPROACH TO ANOMALY DETECTION

Fusion diagnostics translate physical behaviours into reproducible structural shapes in the signals. Studying the phenomena of interest typically requires building specific databases to focus the data analysis process on the problem at hand. To this end, specific patterns (*i.e.* physical events) have to be found inside massive databases.

In general, pattern location has been historically carried out in a manual way. This searching process becomes intractable in large databases or under long pulse conditions. The proliferation of

diagnostics that use cameras creates an even worse situation with regard to stored information and pattern location.

The automatic search of physical events in signals has been recently considered for nuclear fusion environments. A novel and universal technique, Universal Multi-Event Locator (UMEL), allows the automatic location of events in waveforms and video-movies This approach is based on support vector machines regression estimations to identify and locate particular signatures in the signals such as edges, peaks or textures. These footprints allow the characterization of local information either in the time (or space) domain or in the frequency (or spatial frequency/wave number) domain or in both.

Simple linear regression consists of minimizing a regularized error function. To obtain sparse solutions in the case of SVM regression, the quadratic error function is replaced by an e-insensitive error function [15]. This defines a region which provides zero error if the difference between the regression estimation and the target value is less than μ.

The SVM regression presents two different types of support vectors, the ones which are inside the insensitive region and the ones which are outside this region. The support vectors which lay outside the insensitive region are called external support vectors and can be interpreted as the symptom of particularly abrupt changes in the behaviour of the signal. This is the interpretation proposed in [6] for time series and applied to images in this paper. The number of external support vectors is indeed an indication of significant changes in the appearance of an individual frame with respect to the average frame in the same video. This is shown graphically in figure 8. The images, which present features significantly different from the typical frames, are characterised by a high number of external support vectors. The number of external support vectors allows therefore identifying the frames in which something anomalous is present in the image. The number of external support vectors can be used as an anomaly detector. The advantage of this solution is, among other things, its absolute generality. The approach can be applied to any type of image and is equally useful in analysing other types of signals, such as time series.

Figure 9 top shows the temporal evolution of the number of external support vectors with an infrared camera of JET (Pulse No: 70231). The bottom plot identifies the frames with higher IR activity in an automatic way with UMEL.

CONCLUSIONS AND FUTURE PROSPECTS

New image processing tools are indispensable in MCNF to safety operate the next generation of devices and to maximize their scientific exploitation. The peculiarities of videos of high temperature plasmas require further developments. The suitable advances range from image processing (an image as input to the analysis process to provide an image as output), to image analysis (an image as input to provide a quantitative measurement as output) and image interpretation (an image as input to achieve a high level of interpretation as output). Particular attention will have to be devoted to the extraction of useful information in real time. Further progress would be also very desirable in

the field of anomaly detection. From the point view of the hardware, parallel computation and radiation hardness are certainly some of the major issues for the future.

ACKNOWLEDGMENTS

This work, supported by the European Communities under the contract of Association between EURATOM/CEA/CIEMAT and ENEA, was carried out under the framework of the European Fusion Development Agreement. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

REFERENCES

[1]. John C. Russ "The image processing handbook" CRC Press Taylor and Francis Group 5th edition 2007.

[2]. Richard Layne, Martin Wheatley, "New data storage and retrieval systems for JET data", Fusion Engineering and Design, Volume **60**, Issue 3, June 2002, Pages 333-339, ISSN 0920-3796, DOI: 10.1016/S0920-3796(02)00029-7.

[3]. Chen, Pau & Wang (Eds.) Handbook of pattern recognition & computer vision. World Scientific. pp. 163 - 209. ISBN 981-02-1136-8

[4]. L. Chua, T. Roska, "Cellular neural networks and visual computing: Foundations and applications", Cambridge University Press, Cambridge, 2004.

[5]. M.Sonka, V.Hlavac, R.Boyle "Image processing, analysis and machine vision" Thomson, London, 2008 Third edition.

[6]. J. Vega, A. Murari and S. González. "A Universal support vector machines based method for automatic event location in waveforms and video-movies: Applications to massive nuclear fusion databases". Rev. Sci. Ins. **81**, 023505 (2010) 11pp.

[7]. E.Gauthier et al. Fusion Engineering and Design, Volume **82**, Issues 5-14, October 2007, Pages 1335-1340.

[8]. Z. Nagy, P. Szolgay, "Configurable Multi-Layer CNN-UM Emulator on FPGA", IEEE Trans. on Circuits and Systems I: Fundamental theory and applications, Vol. **50**, pp. 774-778, 2003.

[9]. B. Lipschultz, J. Nucl. Mater. 145-147 (1987) **15**.

[10]. M. K. Hu, IRE Trans. Info. Theory, vol. IT-8, pp.179–187, 1962.

[11]. B. Lucas, T. Kanade, "An iterative image registration technique with an application to stereo vision". *In Proc. Seventh International Joint Conference on Artificial Intelligence*, Vancouver, Canada, 1981, pp. 674–679.

[12]. B. Horn, B. Schunck,–"Determining optical flow", *Artificial Intelligence*, vol. **17**, pp.185–203, 1981.

[13]. A. Bruhn, J. Weickert, C. Schnorr, "Lucas/Kanade meets Horn/Schunck: combining local and global optic flow methods", *Int. J. Comput. Vision*, vol. **61**-3, 211-231, 2005.

[14]. T. Craciunescu, A. Murari, A. Alonso, P.T. Lang, G. Kocsis, I. Tiseanu, V. Zoita., "Application of Optical Flow Method for Imaging Diagnostic in JET", Journal of Nuclear Material, to be published

[15]. C.M.Bishop "Pattern recognition and Machine Learning" Springer, Singapore 2009

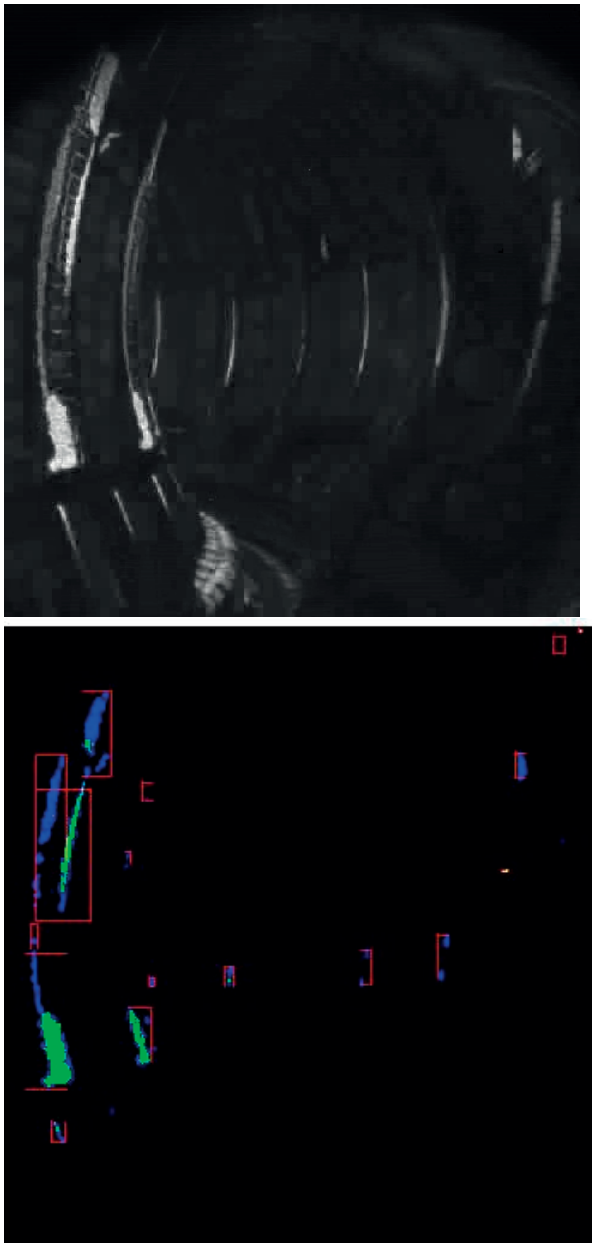

Figure 1: Top-Example of images acquired by JET IR wide angle camera. The white pixels indicate regions of high surface temperature. Bottom- Example of hot spots detected by the serial algorithm.

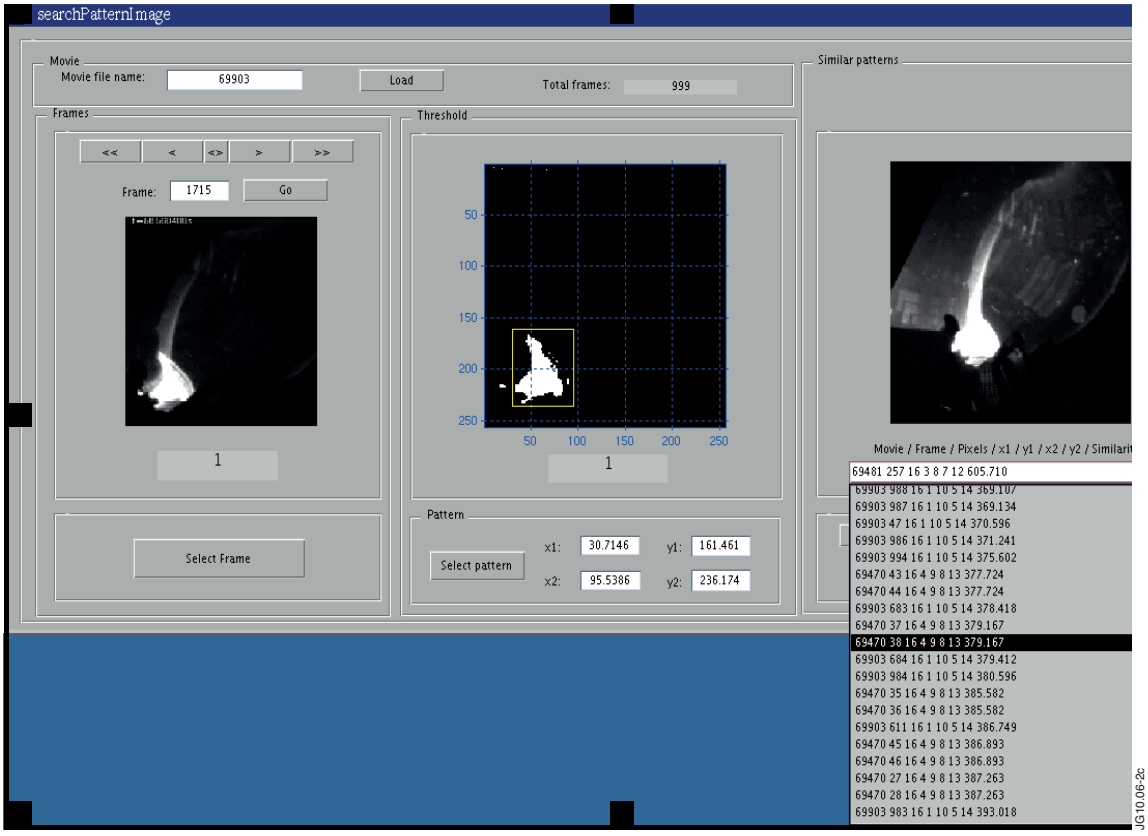

Figure 2: An example of retrieval of patterns within images using the structural pattern recognition approach described in the paper. The object to search for is selected with the cursor by the user (central image) in a generic frame. The pattern recognition algorithms identify the frames in the database, which contain the same or similar objects. An example of these frames with similar patterns and their list is shown on the right part of the figure).

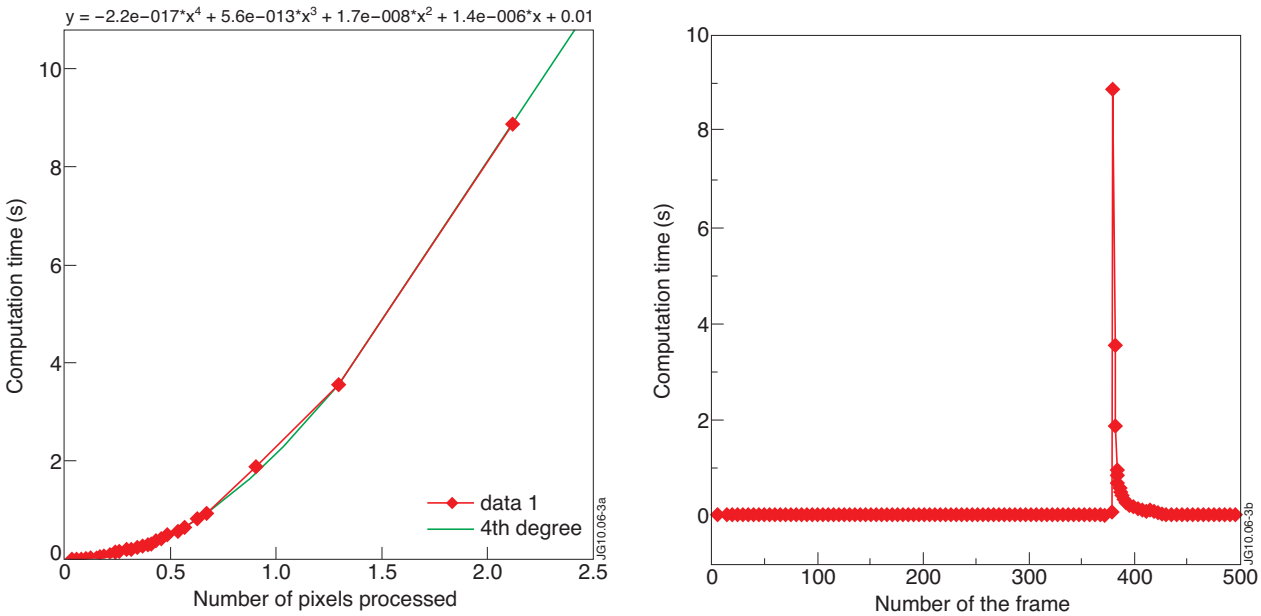

Figure 3: Computational time of the serial algorithm in C++ tested on 11300 frames of JET wide angle cameras. Top - the dependence of computational time from the number of hot pixels (pixels whose temperature is above the alarm threshold); the experimental value and theoretical model expressed as a four order polinomial are compared Bottom - evolution of the computational time per frame in the IR video of one JET discharge.

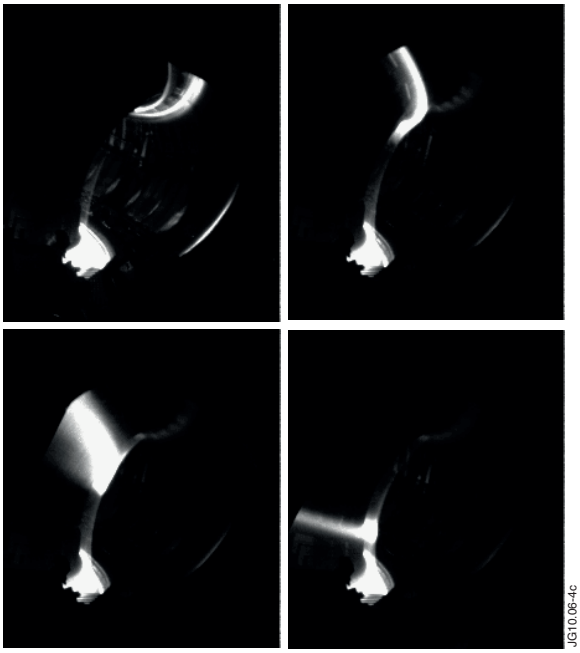

Figure 4: Sequence of frames taken by JET fast visible camera showing the MARFE evolution along the inner wall of JET vacuum vessel.

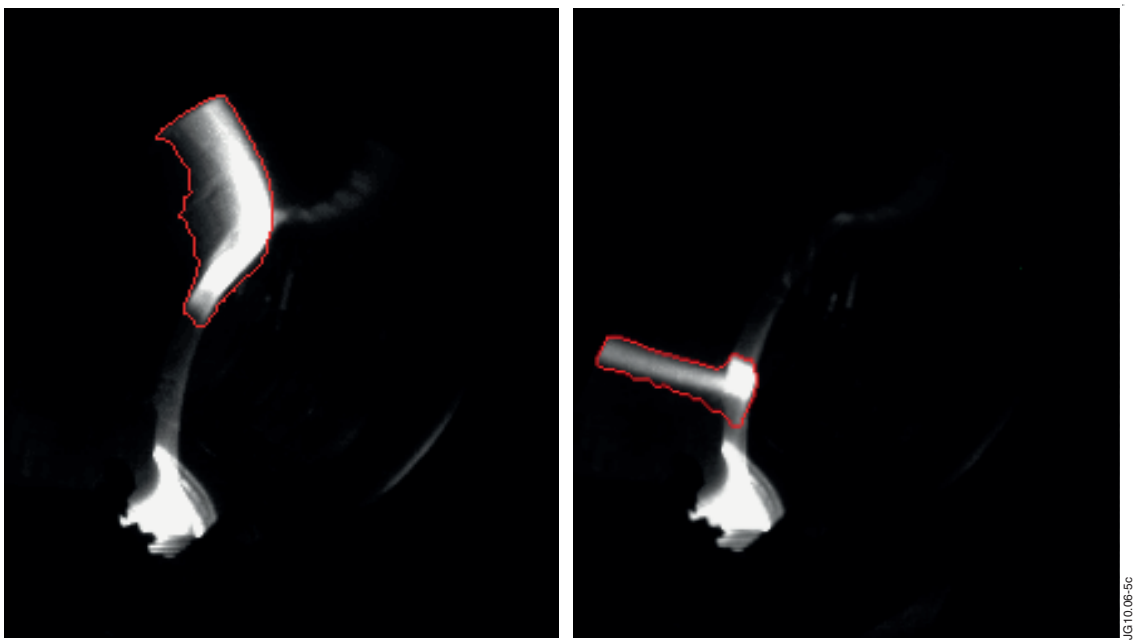

Figure 5: Examples of a MARFE properly identified by the described algorithm.

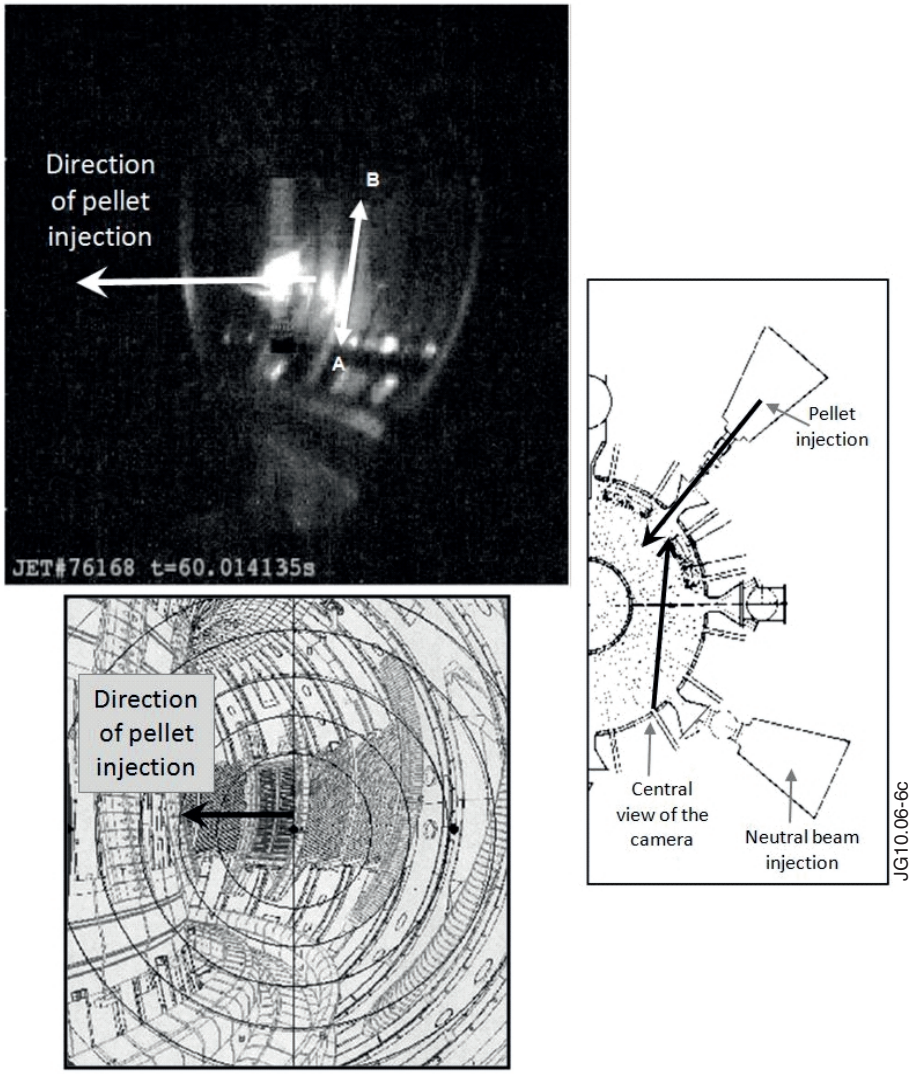

Figure 6: Top: view of the pellet ablation cloud as seen by JET fast visible camera Bottom: the field of view of the fast camera with an arrow indicating the pellet nominal trajectory. Right: a top view of JET vacuum vessel giving the topology of the pellet injector with respect to the field of view of the fast camera. The pellet speed estimated with the optical flow is of 215 ± 12 m/s: the nominal speed of the injected pellets is 240 ÷ 262 m/s.

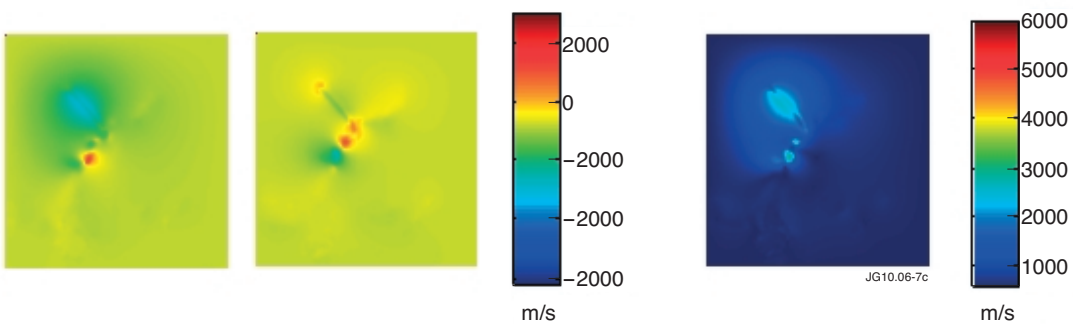

Figure 7: Optical flow calculation of the speed of the MARFE in Fig.4 top-right. Horizontal speed component (left), vertical speed component (middle) and speed modulus (right).

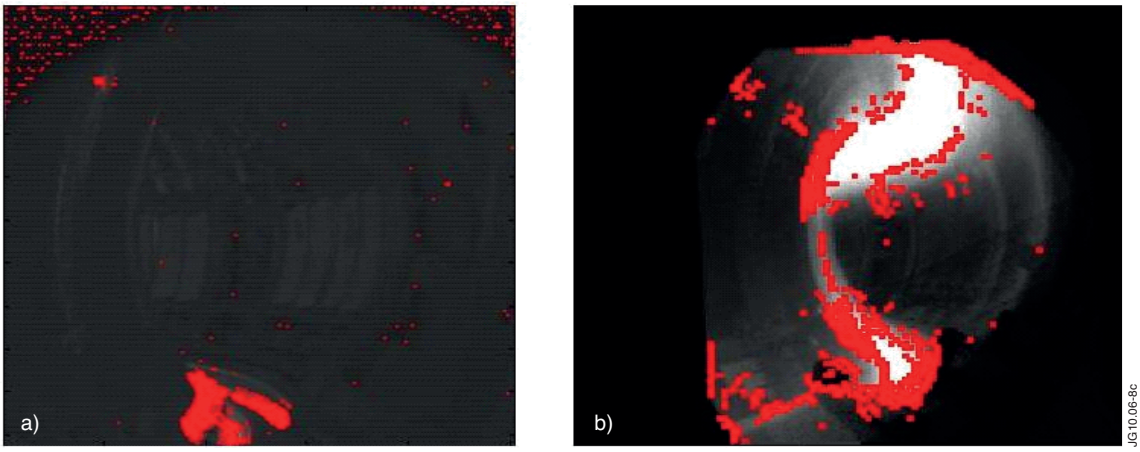

Figure 8: In these two images it appears very clearly how the external support vector crowd around the regions of high gradients in the pixel intensity.

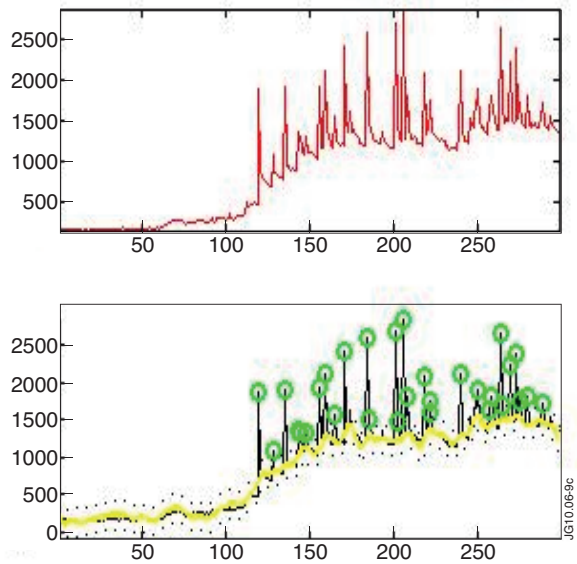

Figure 9: Frames with a greater Number of external support vectors denote higher IR activity