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3D infrared temperature maps measurements of ablative materials during plasma wind tunnel experiments

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Abstract
Accurate surface temperature and recession measurements are crucial experimental data for plasma wind tunnel testing of ablative thermal protection materials. In this work we propose a novel methodology to reconstruct infrared temperature maps on 3D geometries undergoing surface recession. An optical calibration technique is used to extract 3D metric information from the 2D thermal images, thanks to a specific calibration target with control points. The evolution of the sample shape during the experiment is tracked from a side view, using a visual-range camera with dedicated image processing, and reconstructed in 3D under the assumption of axisymmetry. The surface temperature is projected on the time-varying 3D geometry from the calibrated thermograms. The technique is demonstrated on a graphite ablation experiment in air plasma. The reconstructed maps provide detailed multidimensional information about the transient temperature evolution, overcoming traditional approaches that are limited around the stagnation point. The technique allows to study ablation mechanisms with further detail, improving experimental data for material qualification and validation of simulation codes.

Keywords: infrared thermography, 3D imaging, ablation, plasma wind tunnels

(Some figures may appear in colour only in the online journal)

1. Introduction
The hypersonic flight of a spacecraft through a planetary atmosphere is a fascinating engineering endeavor, often representing the most critical part of a space mission. During atmospheric entry, the conversion of vehicle’s kinetic energy into thermal energy of the flow across the shock wave creates an extreme aerothermal environment. Thermal protection systems (TPSs) are needed to shield the spacecraft from the severe heat loads \cite{1}. In the case of ablative TPSs, the high-temperature, chemically-reacting flow leads to thermo-chemical degradation of the material. As multiphase ablation processes and aerothermodynamic phenomena are still poorly understood, ground testing in plasma wind tunnels (PWTs) becomes crucial for material qualification and validation of predictive tools.

During ground testing, a representative material sample is exposed to a plasma flow in similar conditions to those encountered during atmospheric entry \cite{2}. Accurate experimental measurements of the sample surface temperature and ablation behavior are essential both to characterize the material response and to develop computational tools for predicting their performance. In this context, infrared (IR) thermography is a powerful means to perform temperature measurements in PWTs: it is a non-intrusive optical technique, characterized by high sensitivity, low response time and it is two-dimensional \cite{3,4}. Despite the promising advantages, two main difficulties

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have to be considered. Firstly, IR data are available in the form of 2D images, while the observed test object surface is often non-planar. Hence, the application of simple linear magnification factors is not suitable and the precise spatial reconstruction of the temperature maps becomes a critical task. Secondly, as the material sample interacts with the high-temperature, chemically-reacting plasma flow, surface recession and shape change can occur. Hence, a suitable technique should be used to track the moving surface and to account for this information when performing the 3D reconstruction.

The first point can be addressed by optical calibration (OC) techniques, which first evolved in the field of computer vision [5–10] to extract 3D metric information from 2D images and found later application in wind tunnel metrology. In this regard, some early examples were reported by Donovan et al [11], Bell and McLachlan [12] and Le Sant et al [13, 14], who used a linear perspective projection for the spatial calibration of pressure and temperature sensitive paint measurements. The latter authors successively pioneered the application of OC methods to IR thermography for heat flux measurements [15, 16]. More recently, Cardone et al [17] developed a static OC technique for IR thermography to study the shock-wave/boundary-layer interaction in hypersonic flows. 3D temperature maps were reconstructed on a double cone geometry using a planar calibration pattern and accounting for the directional emittance. Zaccara et al [18] later extended this methodology to measure the multi-dimensional heat transfer coefficient over a cone at Mach 6. Notably, Hellstein and Szwedo [19] combined a 3D scanner with IR thermography for real-time reconstruction of 3D temperature maps in non-destructive testing of composite structures. However, application of such techniques to PWT experiments is scarce in the literature: radiometers are typically used to measure temperature around the stagnation point [20, 21] while IR thermography, lacking a spatial calibration, usually provides only some qualitative information from the 2D image [22–26]. Hence, 3D temperature maps reconstruction is highly desirable to provide accurate and spatially calibrated measurements.

Concerning the surface recession of the material sample, several measurements techniques have been proposed in the literature. Stereo-camera photogrammetry found recent application for in situ ablation metrology in plasma [27–29] and hypersonic [30] wind tunnels. Eberhart et al [31] used plenoptic metrology for three-dimensional in situ measurement of meteorite ablation and shape change in an arc-jet facility. Recently, Liu et al [32], developed a system based on a single camera and a digital-micromirror-device projector with structured laser light to perform in situ 3D shape measurements in a PWT. Despite the advanced performances, these techniques often require complicated set-up and post-processing tools. Moreover, photogrammetric methods are mostly limited by the demand for sufficient local contrast and surface texture, making them hardly applicable for smooth or semi-transparent surfaces. Side-view camera imaging with edge-detection algorithms, instead, offers a rather simple and robust method for in situ recession measurements, as demonstrated by Helber et al [21] for carbon ablators and by Bianchi et al [33] for low-temperature ablators, making this a valuable candidate for the present study.

In this paper we build on our previous findings [34, 35] to develop a robust technique for IR metrology in PWTs that allows to reconstruct time-resolved three-dimensional temperature maps over the ablating surface of a material sample exposed to the plasma flow. The novelty of this work exists in two main aspects. First, OC methods are applied to IR thermography in PWT experiments (section 3), allowing precise spatial calibration and 3D reconstruction over non-planar surfaces. Second, the traditional static-target reconstruction is overcome by a dynamic tracking of the sample surface through in situ side-view camera imaging (section 4). Under the assumption of axisymmetric recession, the sample shape is reconstructed in 3D. The information obtained from the two techniques is then combined to achieve time-resolved 3D temperature maps measurement over the ablating sample surface. The technique is demonstrated on a hemispherical graphite sample exposed to air plasma (section 5), obtaining 3D temperature maps for different ablated shapes of the material. The temperature in the stagnation region is finally validated against a simultaneous measurement by means of two-color pyrometry.

This methodology expands the in situ metrology capabilities of PWT material testing by providing quantitative temperature data over the surface of the test sample as its recedes due to thermochemical ablation. In particular, we overcome the limitation of traditional experimental approaches which are restricted around the stagnation point region, thus providing further insight into the transient thermal response and ablation behavior, both for material qualification and for validation of simulations codes.

2. Experimental facility, test material and measurement set-up

2.1. The VKI Plasmatron facility

The VKI Plasmatron features a 160 mm diameter Inductively Coupled Plasma (ICP) torch, powered by a 400 kHz, 1.2 MW, 2 kV electric generator [36, 37]. Figure 1(a) shows a sketch of the experimental set-up, which is detailed hereafter. The electric power to the coil (Pd) is monitored by a voltage-current probe. A calibrated flow meter from Bronkhorst (F203AV) controls the mass flow rate (m_gas) of the test gas supplied to the torch. The gas, compressed atmospheric air in this case, is heated by electromagnetic induction, thus providing a chemically pure plasma flow. Pressure in the test chamber (p_c) is measured by an absolute pressure transducer (Membranovac DM 12, Leybold Vacuum). Characterization of the plasma flow conditions is performed by means of intrusive measurements of stagnation point heat flux (q_{stagn}) over a reference catalytic surface and jet dynamic pressure (p_{dyn}) through a Pitot probe [38]. A spectograph records locally-resolved emission spectra to measure temperature profiles across the plasma jet and rebuild the flow enthalpy at the boundary layer (BL) edge (h_e), under the assumption of local thermodynamic...
equilibrium [39]. The main parameters describing the test conditions presented in this work are reported in table 1. As far as the application of IR thermography is concerned, these parameters do not have a direct impact on the present study; however, they characterize the conditions of the plasma jet in our facility and are useful to reproduce the experiment discussed in this work.

2.2. Ablative material sample and test procedure

The ablative material sample was a 50 mm diameter hemisphere with a 15 mm long cylinder, machined out of a fine extruded graphite rod (grade GR008G, Graphitestore, Northbrook, Illinois, USA), with a density of 1.76 g cm$^{-3}$. Graphite was selected since it typically offers a steady ablation behavior in air plasma, where surface recession is mainly promoted by oxidation of solid carbon by atomic and molecular oxygen [21]. The sample was glued to an alumina-silica insulator and mounted onto a cooled probe arm through a graphite support, as shown in figure 1(b). The probes were positioned inside the test chamber at a distance of 385 mm from the ICP torch exit and the placement ensured accurate alignment with the torch axis. After reaching the desired test conditions in terms of chamber pressure and electric power, the cold-wall heat flux and jet dynamic pressure were measured. Successively, the sample was injected into the plasma flow and the torch was switched off after 640 s.

2.3. IR measurement set-up

We used the FLIR A6750sc (Teledyne FLIR LCC, Wilsonville, Oregon, USA) IR camera, featuring an InSb detector, with a sensitive spectral range within 1 − 5.5 μm, and a resolution of 640 × 512 pixels. The camera is equipped with a 50 mm lens, with a reduced transmission range between 3 − 5.3 μm, and a neutral density filter, which allows measurements up to a radiance temperature of 3000°C. IR frames were recorded at a frequency of 2 Hz. The camera was placed at ~1.1 m distance from the test sample, with an inclination of ~45° with respect to the jet axis. Optical access to the Plasmatron chamber was provided through a 1.5 cm thick thallium-bromoiodide (KRS5) window, offering a transmission around 70% in the camera wavelength range. The field of view at the sample distance resulted in a magnification factor of about 0.3 mm/pixel on a planar target. The radiometric calibration of the IR camera is discussed in section 2.4.

The Marathon Series MR1SC (Raytek Corporation, Santa Cruz, California, USA) two-color pyrometer was used to record the sample surface temperature around the stagnation point ($T_{stag}$), providing a comparison to the temperature measured by means of IR thermography. The instrument features a wafer silicon detector, allowing simultaneous recording in two closely-spaced IR bands, between 0.75–1.1 μm and 0.95–1.1 μm. Under the assumption of grey emittance between the two bands, commonly adopted in multi-spectral pyrometry, the ratio of the signals depends only on temperature [40]. The instrument is placed at ~1 m distance from the sample, with an inclination of ~35° with respect to the jet axis, and the probing volume over the sample surface has an estimated size of 14 mm in diameter. Optical access to the test chamber is provided through a 1 cm thick quartz window, whose spectral transmission can be considered flat in the instrument range. Calibration was outsourced to the National Physics Laboratory (NPL, UK) up to a radiance temperature of 3000°C.

Table 1. Plasmatron experimental conditions for the test reported in this work, listing the electric power to the coil $P_{el}$, test gas mass flow rate $\dot{m}_{gas}$, chamber pressure $p_c$, BL edge enthalpy $h_e$, cold-wall heat flux $\dot{q}_{cw}$ and dynamic pressure $p_{dyn}$.

<table>
<thead>
<tr>
<th>distance (mm)</th>
<th>duration (s)</th>
<th>$P_{el}$ (kW)</th>
<th>$\dot{m}_{gas}$ (g s$^{-1}$)</th>
<th>$p_c$ (mbar)</th>
<th>$\dot{q}_{cw}$ (MW m$^{-2}$)</th>
<th>$p_{dyn}$ (Pa)</th>
<th>$h_e$ (MJ kg$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>385 ± 1</td>
<td>640</td>
<td>225 ± 10</td>
<td>16 ± 0.15</td>
<td>100 ± 2</td>
<td>1.44 ± 140</td>
<td>35 ± 5</td>
<td>25.73 ± 1.7</td>
</tr>
</tbody>
</table>
A radiometric calibration of the IR camera is necessary to convert the measured signal intensity counts to a temperature value, accounting for the material effective directional band emittance and for the transmittance of the optical path. Neglecting ambient reflections and optical path emission for the high object temperatures encountered in our application, typically larger than 750 K, the detected band radiant power per unit instrument throughput, \( \Phi_{\text{det}} \), can be approximated from the IR camera measurement equation [4, 17, 41] as

\[
\Phi_{\text{det}} \approx \tau_{\Delta \lambda} \varepsilon_{\Delta \lambda}(T, \alpha) \Phi^{\text{bb}}(T),
\]

where \( \tau_{\Delta \lambda} \) is the effective band transmittance of the optical path, \( \varepsilon_{\Delta \lambda}(T, \alpha) \) is the effective directional band emittance of the target object, possibly dependent on its temperature \( T \) and IR camera view angle \( \alpha \), while \( \Phi^{\text{bb}}(T) \) is the band radiant power per unit instrument throughput sensed by the IR camera for a blackbody source at temperature \( T \). The view angle \( \alpha \) is defined as the angle between the viewing ray direction of the camera and the local normal to the object surface, later discusses in section 3.3. Letting \( R_{\lambda} \) be the normalized spectral response of the IR camera, provided by the manufacturer (figure 2(a)), including detector sensitivity and internal optics (lens and filter) transmission, we have

\[
\Phi^{\text{bb}}(T) = \int_0^\infty R_{\lambda} L^{\text{bb}}_{\lambda}(T) \, d\lambda,
\]

where \( L^{\text{bb}}_{\lambda}(T) \) is the spectral radiance of a blackbody at temperature \( T \). Finally, the measured signal intensity counts \( U \) are proportional to the detected band radiance as

\[
U = C(\Phi_{\text{det}}),
\]

where \( C \) is the radiometric calibration curve. Although this is typically close to a linear function, a quadratic fit usually helps to reduce the fitting residuals and accounts for the instrument non-linearity.

The calibration was performed in-house with a reference blackbody source (Landcal R1500T, Ameteck-Land, Sheffield, UK) up to a temperature of 1773 K, reproducing the optical path of the measurement set-up and assuming a unit spectral emittance of the source. Figures 2(b) and (c) show the radiometric calibration diagrams, including the quadratic fit of the data points along \( C \) and its extrapolation up to 6050 count, i.e. the maximal signal intensity observed in our experiment. The transmittance of the atmosphere was neglected and a value of \( \tau_{\Delta \lambda} = 0.7 \) was used to account for the KRS5 window.

Then, starting from the measured signal intensity \( U \) during the experiment, once the temperature and angular dependence of \( \varepsilon_{\Delta \lambda} \) are known, the model of equations (1) and (3) can be iteratively solved for \( T \). Concerning \( \varepsilon_{\Delta \lambda}(T, \alpha) \) for graphite, Neuer [42] reported a value around 0.85 in the 3-5 \( \mu \)m range, which was fairly independent of temperature between 1375 K and 2025 K. Based on the data of Wang et al [43], we consider the angular variation of \( \varepsilon_{\Delta \lambda} \) negligible up to \( \alpha = 60^\circ \). In this regards, the OC of the IR camera will allow to measure the view angle and select a suitable region on the sample surface (section 3.3).

\[\ldots\]
the context of this work the observed surface recession is relatively slow, HSC imaging offers very low integration times and fast auto-exposure, which help to improve the image contrast. The camera features a $1240 \times 680$ pixels CMOS detector, with a spectral response from the ultra-violet to the near-IR wavelength range. Frames are recorded at 100 Hz. A stack of neutral density filters were used to attenuate the strong radiative emission from the sample and to avoid sensor saturation. The camera was mounted at a distance of 220 cm from the jet axis and a 400 mm optics was used to provide a suitable field of view. A three-axis laser level was used to ensure precise alignment and orthogonality to the jet axis and a planar checkboard provided a reference calibration pattern prior to the experiment. Complementary measurements confirmed a negligible effect of parallax.

The instruments were connected to a common data acquisition unit and triggered with a reference signal, which allowed to synchronize the two-color pyrometer with the IR camera and HSC frames.

3. OC of the IR camera

In computer vision, the OC of a camera is a necessary step to extract 3D metric information from 2D images [8]. This typically includes intrinsic parameters, describing some optical characteristics of the camera apparatus, as well as extrinsic parameters, such as the relative position and orientation of the camera with respect to the object of interest. The pinhole camera model is the most widely adopted, while existing methods mainly differ due to the characterization of the lens distortion [5] and the solution algorithms [7]. Multi-step methods, such as the ones introduced by Tsai [6], Weng et al [7] and Heikkila [9, 10], are the basis of the modern approach to the camera calibration. The OC model adopted in this work exploits the camera calibration tool available in the Open Source Computer Vision Library (OpenCV) [44], which is based on the pinhole camera model with lens distortion described hereafter.

3.1. Model

The pinhole model approximates the camera imaging optics, where each point in the object space is projected by a straight line through the projection center onto the image plane, as illustrated in figure 3. The real-world coordinate frame is indicated with $F_R$ and the $X$-axis coincides with the plasma jet axis in our application. The center of projection is the origin of the camera frame $F_C$. The image plane $\Pi$ is parallel to the $x$-$y$ plane, at a distance $f$ (focal length) from the projection center along the $z$-axis. This is also called optical axis and its intersection with the plane $\Pi$ is called principal point. The axes $u$ and $v$ of the 2D image frame $F_I$ are parallel to the $x$ and $y$ axes and, as usually adopted in computer vision literature, the origin of the image coordinate system is in the upper left corner of the image array and the unit of the image coordinates is pixels. The coordinates of the principal point in $F_I$ are $[u_0, v_0]$.

The object point on the sample target (ST) has coordinates $X = \{X, Y, Z\}^T$ in $F_R$ and $x = \{x, y, z\}^T$ in $F_C$, while its projection is $u = [u, v]^T$ in $F_I$. The transformation between $F_R$ and $F_C$ can be formulated as a rigid roto-translation

$$x = RX + t,$$

where $R$ is the rotation tensor and $t$ is the translation vector. Since $R$ is orthonormal, it can be described by three Euler angles. Together with the three components of $t$, they represent a total of six extrinsic parameters.

Neglecting lens distortion effects for the moment, the projection of the point coordinates from $F_C$ to $F_I$ is a simple scaling by a factor $f/z$, followed by a translation relative to the principal point $[u_0, v_0]$, as

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} Df \xi f/z \cdot x + u_0 \\ Df \zeta f/z \cdot y + v_0 \end{bmatrix},$$

(5)

where the magnification factor $D$ is introduced to convert the camera coordinates, usually in millimeters, to the image coordinates in pixels, while the pixel aspect ratio $\xi$ accounts for uneven metrics in the $u$ and $v$ components. Hence, introducing the scaled coordinates $x' = x/z = [x/z, y/z, 1]^T$, the image coordinates can be written as

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \xi Df & 0 & u_0 \\ 0 & Df & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x/z \\ y/z \\ 1 \end{bmatrix} = Ax',$$

(6)

where $A$ is called camera intrinsic matrix and the parameters $f$ (or equivalently $D \cdot f$), $\xi$, $u_0$ and $v_0$ represent four intrinsic parameters of the pinhole camera model. Lens distortion is accounted for with three radial coefficients, $k_1$, $k_2$ and $k_3$, and two tangential coefficients, $p_1$ and $p_2$, by introducing a correction term $\Delta u$ and $\Delta v$ to the previous equation.

**Figure 3.** Sketch of the pinhole camera model adopted by the OpenCV camera calibration tool [44], highlighting the real world frame $F_R$, the camera frame $F_C$ and the image frame $F_I$. A point $X = \{X, Y, Z\}^T$ on the sample target is projected to the image frame coordinates $u = [u, v]^T$ through a straight line originating at $F_C$. 

$$X = [X, Y, Z]^T$$
and \( p_2 \). The distorted coordinates in the image frame are finally given by \( \mathbf{u} = A \mathbf{x}' \), with the following additional transformation [44]

\[
x'' = \mathcal{D}(x', k_{1:3}, p_{1:2}) = \left[ \begin{array}{c} x' \cdot (1 + \sum_i k_i r^{2i}) + 2p_1 x' y' + p_2 (r^2 + 2x'^2) \\ y' \cdot (1 + \sum_i k_i r^{2i}) + p_1 (r^2 + 2y'^2) + 2p_2 x' y' \end{array} \right],
\]

where \( r^2 = x'^2 + y'^2 \) and \( \mathcal{D} \) represents an explicit approximation of the Brown-Conrady distortion model shown in [10].

Overall, the model can be synthetically expressed as \( \mathbf{u} = \mathcal{P}(\mathbf{X}) \) and consists of six extrinsic and four intrinsic projection parameters, along with five distortion coefficients. The objective of the camera calibration procedure is to determine optimal values for these parameters starting from image observations of a known calibration target (CT).

### 3.2. CT

The CT should offer precisely known coordinates of some reference points \( \mathbf{X}_{\text{CT}} \) in \( \mathcal{F}_R \), whose position \( \mathbf{u}^{\text{CT}} \) can be also detected in image frame \( \mathcal{F}_I \). Mainly two techniques have been reported in the literature: either using an independent object [9, 10, 17], such as a planar target, or embedding the calibration points directly in the ST [13, 14]. The former option, despite offering larger design flexibility, requires to accurately measure the relative position and orientation between the CT and the ST, which can be a tedious task for applications in large wind tunnels. For the latter, instead, this is not necessary since they physically coincide. Moreover, a three-dimensional pattern requires only a single calibration view [10] and more than 15 control points are required to over-constrain the calibration model [17]. In addition, the markers should be detectable in the IR light for thermography applications. Both low conductivity inserts [15, 16] or cavity holes [17] were proposed to offer the desired IR contrast.

In the context of this work, we designed a specific CT that combines the advantages of the aforementioned techniques for PWT applications. It consists of an aluminum cap featuring 61 1.5 mm diameter holes, drilled at known positions, as shown in figure 4(a). The cap has a precisely machined shape, complementary to the ST, and it is placed on it before the experiment to acquire a calibration thermogram (figure 4(b)). This procedure ensures that the CT is installed at the same location of the ST. The thickness of the CT is also accounted for. IR contrast is achieved through the higher emissance of the cavities with respect to the surrounding aluminum and by additional pre-heating of the sample by means of a portable heat gun. We exploit image processing tools available in the OpenCV library for their automatic detection with subpixel precision.

![Figure 4. Picture of the calibration target (a) and corresponding IR thermogram (b). The calibration target is placed onto the sample target before the experiment, thus ensuring that their location coincides for the optical calibration. The calibration markers become visible in the IR image thanks to the increased emission from the cavity holes, further enhanced by the heated sample underneath.](image)

### 3.3. OC metrics

Due to the non-linear nature of the OC model, the solution of the problem requires an iterative algorithm and the Levenberg-Marquardt method has been shown to provide the fastest convergence [5, 17]. The re-projection error \( e_i \) is defined as the vector difference between the detected image coordinate of the \( i \)th calibration marker and its projection using the OC model

\[
e_i = \mathbf{u}_i^{\text{CT}} - \mathcal{P}(\mathbf{X}_i^{\text{CT}}).
\]

The method minimizes the root-mean squared (RMS) value, \( \sigma_{\text{RMS}} = \sqrt{\sum e_i^2 / N} \), over the \( N \) calibration points.

Once the calibration is performed, the angle of view of the IR camera with respect to the local normal to the ST surface can be computed. The view vector, \( \mathbf{v} \), identifies the viewing ray direction of each camera pixel to the correspondent point on the ST, represented by the red line in figure 3. Since in our application \( x/z \approx 1 \) and \( y/z \ll 1 \), and the lens distortion is typically small, then \( \mathbf{v} \) can be approximated by the \( z \)-axis (optical axis) with a negligible error. This is typically less than 0.5° in our application. Hence, the inverse transform

\[
\mathbf{V} = \begin{bmatrix} R^T \mathbf{I} & -t \end{bmatrix} \begin{bmatrix} \mathbf{v} \\ 1 \end{bmatrix}
\]

allows to find the view vector \( \mathbf{V} \) in \( \mathcal{F}_R \), where \( \mathbf{I} \) is the identity tensor. Once a triangulation of the ST surface is built (section 4.3), indicating with \( a_i, b_j \) and \( e_i \) be the vertices of the \( j \)th triangle element, the normal vector \( \mathbf{n}_j \) to its surface is computed as

\[
\mathbf{n}_j = (b_j - a_j) \times (e_j - a_j).
\]

If \( m_j \) is the position of the cell center of the \( j \)th triangle, then \( s_j = \mathbf{V} - m_j \) identifies the view vector to each surface element. The angle of view \( \alpha_j \) is then computed as
\[ \alpha_j = \cos^{-1}\left( \frac{n_j \cdot s_j}{||n_j|| ||s_j||} \right). \]  

Then, \( \alpha_j \) can be used to correct the thermograms for the angular-dependent band emittance or to select an adequate region over the ST surface where this can be neglected, if possible.

4. Dynamic target tracking

While the parameters describing the transformation \( \mathcal{P} \) are valid as long as the IR camera is kept fixed, the coordinates \( X(t) = [X(t), Y(t), Z(t)]^T \) of the ST surface points in \( \mathcal{F}_R \) change in time due to surface recession and an additional measurement is required to track their evolution. With a relatively simple set-up and analysis tools, side-view camera imaging offers a robust technique for \textit{in situ} shape and recession measurements on ablative materials [21, 33]. We adopt the following method: after OC of the HSC, edge detection algorithms are applied to the recorded frames to extract the sample shape in the X-Y plane; under the assumption of axisymmetry, the three-dimensional object surface can be inferred from the observed two-dimensional side view.

4.1. OC of the HSC

In principle, similar equations to the ones presented in section 3.1 have to be used for the OC of the HSC. Here we use a tilde to indicate the HSC image coordinates \( \tilde{u} = [\tilde{u}, \tilde{v}]^T \), frame coordinates \( \tilde{x} \), focal length \( f \) and magnification factor \( D \) in the camera frame, while the real-world coordinates \( X \) are unique. In this case, the camera captures a side view and a three-axis laser level is used to align the optical axis (\( \tilde{z} \)-axis) perpendicularly to the X-Y plane of \( \mathcal{F}_R \) (figure 5). As a result, (4) simplifies to \( \tilde{x} = [X, -Y, \tilde{l} - Z]^T \), where \( \tilde{l} \) is the distance between \( \mathcal{F}_C \) and \( \mathcal{F}_R \). Moreover, as we are interested only in the points on the X-Y plane, then \( Z = 0 \) and (5) simplifies to

\[ \begin{bmatrix} \tilde{u} - \tilde{u}_0 \\tilde{v} - \tilde{v}_0 \end{bmatrix} = \begin{bmatrix} \xi \tilde{Df}/\tilde{l}X \\ -\tilde{Df}/\tilde{l}Y \end{bmatrix}. \]  

(12)

Considering the pixel aspect ratio \( \xi = 1 = 1 \), then \( 1/m = \tilde{Df}/\tilde{l} \) is the magnification factor measured in the frame \( \mathcal{F}_R \). Hence, we have

\[ \begin{bmatrix} X(t) \\ Y(t) \\ Z(t) \end{bmatrix} = \begin{bmatrix} \tilde{m} \cdot (\tilde{u}(t) - \tilde{u}_0) \\ -\tilde{m} \cdot (\tilde{v}(t) - \tilde{v}_0) \\ 0 \end{bmatrix}, \]  

(13)

where \( \tilde{m} \) is determined with a calibration checkboard prior to the experiment. Lens distortion effects are considered negligible in this case.

4.2. Edge detection and adaptive masking

Edge detection algorithms, widely applied in image processing and segmentation, evolved to sophisticated methods to achieve high accuracy, non-directionality and low sensitivity to noise [45–47]. We used the sub-pixel edge-detection algorithm proposed by Trujillo-Pino \textit{et al} [48] to detect the image coordinates \( \tilde{u}(t) = [\tilde{u}(t), \tilde{v}(t)]^T \). The method is based on the partial area effect and a second order polynomial approximation is used to locally represent the edges. The algorithm was shown to be accurate in capturing intensity, orientation, position and curvature of the edges. In highly noisy images, an iterative procedure can also be used to increase the accuracy.

For application to PWT experiments, however, low contrast and noise can significantly reduce the detection performance. The recorded light intensity, in fact, is mainly due to the sample self-emission at elevated temperatures, which is typically non-uniform. Spurious light reflection from the plasma torch, as well as localized ablation patterns or oxidation growth phenomena, can degrade the edge-detection performance. To this purpose, we implemented a robust adaptive masking method based on a multi-scale filtering approach to discard the unwanted features in an automatic fashion. This involves the following steps: 1) a pre-filtering with a Gaussian function to reduce the image noise; 2) a Canny edge detection [44, 45] with high threshold, which revealed robust enough to detect the sample outer edges, 3) building a polygonal mask around the edges detected on the first iteration and 4) finally using the sub-pixel method to improve the accuracy of the detected edges.

4.3. Shape fitting and 3D surface triangulation

To use the detected edges from the 2D image for 3D reconstruction, an analytical representation of the shape is highly desired for easier manipulation. This allows to generate the 3D surface mesh with an arbitrary number of points. A combination of a semi-elliptical and polynomials functions, shown in figure 6(a), demonstrated robust and efficient. The
elliptical function also allows to extract additional information, such as the radius of curvature at stagnation point and the drift of the sample center, which help achieving a precise characterization of the ablation behavior. The performance of the fitting can be evaluated by computing the distance of the detected edge points with respect to the fitting curve. Under the assumption of axisymmetry, the fitted shape for \( Y > 0 \) is then revolved around the \( X \)-axis to produce a three-dimensional surface triangulation, as shown in figure 6(b).

5. Results and discussion

We applied the proposed technique to study the transient thermal response and ablation behavior of the graphite sample exposed to atmospheric air plasma. In the following paragraphs we detail each step of the procedure, leading to the reconstruction of the temperature maps on the ablated surface.

5.1. OC of the IR camera

Before the actual experiment, the sample is heated to approximately 100°C by means of a portable heat gun. The calibration cap is then placed onto the ST and a calibration thermogram is acquired after focusing the IR camera. The OC model, described in section 3, is then solved and figure 7(a) shows the components of the re-projection error \( e_i \) in the image frame \( \mathcal{F}_I \). The mean square-root value is 0.289 pixel, while the maximum value is around 0.5 pixel. The marginal plots additionally exclude significant skewness in the statistical distribution of both the \( u \) and \( v \) components, which could otherwise imply a bias in the calibration procedure. Once the OC is performed, the transformation \( \mathcal{P} \) is completely determined and the view angle \( \alpha \) of the IR camera with respect to the local sample surface normal is computed according to (11). Figure 7(b) shows the value of \( \alpha \) on a triangulation of the initial sample surface geometry. Due to the configuration of the optical access to the Plasmatron facility, the view vector has an approximate inclination of 45° with respect to \( X \)-axis and a 45° azimuthal orientation with respect to the \( X-Y \) plane. From this analysis we can identify the triangles on the surface mesh which correspond to \( \alpha < 60° \), that is, a suitable region to perform the 3D reconstruction assuming negligible variation of the angular emittance, as anticipated in section 2.3.

5.2. Analysis of the sample ablation

HSC imaging is used to monitor the evolution of the sample shape during the test from an orthogonal side view. The video is recorded at 100 Hz and under-sampled at 1 Hz since the recession rate is quite low for this experiment. Image contrast becomes sufficiently large to apply edge detection only after 42 s and the analysis shows negligible recession until this moment. Hence, we assume that the initial sample shape is preserved until this time instant. Figure 8(a) shows an example of gray-scale image recorded at the test end (\( t = 640 \) s after injection). The simplified OC, derived in section 4.1, is applied to recorded frames with \( \tilde{m} = 0.1216 \) mm/pixel, obtained with a calibration checkboard prior to the experiment. A three-axis laser level was used to align the sample to the jet axis, thus providing the reference value for \( Y = 0 \). The sub-pixel edge-detection procedure, detailed in section 4.2, is applied and the detected sample edges are then fitted with the proposed
shape functions, as shown in figure 8(b). The fitting performance is evaluated on each frame by computing the error as twice the standard deviation of the distance of the detected edge points with respect to the fitted shape. Figure 8(c) shows that the error increases in time but maintains a maximum value lower than 0.10 mm for the whole test duration. Combining the uncertainty due to the magnification factor and fitting error, the overall uncertainty on the measured sample shape is then ±0.16 mm. The uncertainty on the recession measurement, instead, is estimated to be ±0.22 mm, resulting from the uncertainty on the difference between the instantaneous measured shape and the one measured before the test.

Edge detection is performed on each recorded frame and figure 9(a) depicts the evolution of the fitted sample shape coordinates \([X(t), Y(t), Z(t)]\) in time. We can notice the larger recession at stagnation point \((Y = 0 \text{ mm})\) with respect to the sample sides \(25 \text{ mm} < X < 40 \text{ mm}\). The stagnation point recession, \(\delta_{stag}\), depicted in figure 9(b), shows a linear trend up to about 4.5 mm after 640 s, representing 18% of the sample initial radius. Also shown in the same figure is the recession rate, \(\dot{\delta}_{stag}\), obtained by differentiating a second order polynomial fit of \(\delta_{stag}\). This slightly decreases from 7.9 \(\mu\text{m s}^{-1}\) to 7.5 \(\mu\text{m s}^{-1}\) during the plasma exposure. Finally, the surface recession \(\delta(t)\) can be computed as the distance of the instantaneous shape at time \(t\) with respect to the one at \(t = 0\) s. This is detailed by the plot in figure 9(c), which illustrates \(\delta\) at \(t = 640\) s as a function of the curvilinear coordinate \(s\), originating at the stagnation point. The top surface \((Y > 0 \text{ mm})\) shows a slightly larger recession than the bottom one \((Y < 0 \text{ mm})\), with a maximum deviation of 0.3 mm. Although this would prove an imperfect axisymmetric ablation, the effect is neglected for the scope of this work since the deviation is quite limited.

5.3. 3D temperature maps reconstruction and validation of the stagnation point value

Based on the detected sample shape, a triangulation of the time-varying 3D sample surface geometry is built with a resolution of 60 points along the X-axis and 5° angular spacing in the azimuthal direction. The OC model detailed in section 3.1 allows to project the geometry coordinates from the real-world frame \(F_{R}\) to the IRC image frame \(F_{I}\). Figures 10(a)–(c) show the raw IR thermograms at \(t = 50\) s, \(t = 320\) s and \(t = 640\) s respectively. Also shown are the projected sample silhouette and the orthogonal lines in the X-Y and X-Z planes, whose intersection identifies the location of the stagnation point. We can notice how this drifts significantly in the IRC image frame due to the surface recession, by about 9 pixels in the \(u\) direction and 6 pixels in the negative \(v\) direction. The correspondent 3D reconstructed temperature maps, after correction for \(\varepsilon_{\Delta\lambda} = 0.85\) and calibration, are shown in figures 10(d)–(f) respectively, where we used the PyVista Python package [49] for the visual rendering. One can appreciate how the sample geometry changes in time from the projected orthogonal contours onto the axes grid. The reconstructed temperature maps show the highest value around the stagnation point \((Y = 0 \text{ mm}, Z = 0 \text{ mm})\), decreasing towards the sample sides. An axisymmetric distribution of the temperature field is also noticeable. Neglecting the uncertainty on the value of \(\varepsilon_{\Delta\lambda}\), we estimate an uncertainty of ±2% on the calibrated temperature value.

In figure 11(a), the stagnation point temperature \(T_{stag}\), measured by the IR camera, is validated against the two-color pyrometry measurement in the same region. During the transient heating, \(T_{stag}\) raises to 2250 K in 200 s. After that, it increases slightly to 2280 K as the surface recedes and finally drops sharply after the plasma torch is switched off at 640 s. The two-color pyrometer measurement starts around 1500 K, and the uncertainty on the measured value is estimated in
Figure 8. (a) Gray-scale side-view HSC image of the sample at the end of the test ($t = 640$ s). (b) Shape functions (red lines) closely fit the detected edges (black markers). (c) Evolution of the fitting error in time shows increasing trend but remains smaller than 0.10 mm during the whole test duration.

Figure 9. (a) Evolution of the measured sample shape in time, after edge detection, adaptive filtering and shape fitting. (b) Stagnation point recession ($\delta_{stag}$) shows almost linear trend up to about 4.5 mm after 640 s. Recession rate ($\dot{\delta}_{stag}$) slightly decreases during the plasma exposure. (c) Surface recession profile at 640 s as a function of the curvilinear coordinate from stagnation point ($s$), normalized to the sample initial radius ($R$). The top profile ($Y > 0$ mm) highlights a slightly larger recession with respect to the bottom one ($Y < 0$ mm).

±1.5%. From the comparison, one can appreciate a noticeable agreement between the two signals, which corroborates the IRC temperature measurement.

Finally, from the 3D maps we extract the temperature profiles along the curvilinear coordinate $s$, originating from the stagnation point and running over the sample surface until the side. The profiles are first averaged around the azimuthal angle around the $X$-axis and then normalized to the stagnation point value ($s/R = 0$). From figure 11(b) we can appreciate a similar behavior for the three time instants, with a 15% decrease towards the sample edge ($s/R = 2$). A steeper temperature rise from the hemispherical edge ($s/R = 1$) to the stagnation point is evident as recession progresses towards the end of the test ($t = 640$ s).

Traditional experimental approaches for IR thermography in PWT would be limited to two-dimensional temperature maps in pixel coordinates, obtained after intensity calibration of the data shown in figures 10(a)–(c). The new method presented in this work, instead, allows to extract 3D metric information from the OC and additionally accounts for the moving sample surface (figures 10(d)–(f)). The position and, hence, the temperature at the stagnation point, particularly important for scaling to flight [50], are precisely detected. Moreover, experimental temperature profiles, such as those presented in figure 11(b), can give valuable information for comparison to multidimensional numerical simulations and could not be provided by previous approaches.
Figure 10. Raw IRC frames at $t = 50\, s$ (a), $t = 320\, s$ (b) and $t = 640\, s$ (c), showing the thermal signature of the sample, along with the projected contours and its orthogonal slices in the X-Y and X-Z planes (black lines). (d), (e), (f) Corresponding 3D temperature maps on the ablated sample shape, reconstructed for view-angles smaller than $60^\circ$ deg. Notice the variation in the sample geometry by the projected orthogonal contours on the axes grid.

Figure 11. (a) Comparison between the measured stagnation point temperature ($T_{stag}$) by means of IR thermography (IRC) and two-color (2 C) pyrometry show noticeable agreement, validating correction for $\varepsilon_{\Delta \lambda} = 0.85$. (b) Evolution of the averaged temperature profiles normalized to the stagnation point value ($T(s)/T_{stag}$), along the curvilinear coordinate ($s/R$).

6. Conclusions

During PWT ablation experiments, the sample surface recession and temperature distribution away from the stagnation point are not simultaneously captured up to now. This paper presents a new experimental approach to measure the transient temperature distribution over ablating materials undergoing surface recession. The methodology is based on the OC of IR cameras, allowing the precise spatial reconstruction of the thermographic information over non-planar targets. We
combine this reconstruction with in situ dynamic recession analysis from a lateral view to achieve novel time-resolved 3D temperature mapping within the assumption of axisymmetric recession.

The technique is applied to a graphite ablation experiment in air plasma, where we observe a surface recession at stagnation point reaching about 18% of the initial sample radius. The position of the sample in the image frame drifts significantly, thus proving the need to account for the material ablation in the 3D reconstruction. We achieve an accuracy of \( \pm 0.16 \) mm in tracking the surface position and highlight a non-uniform ablation pattern, which decreases from the stagnation region towards the sides. The small difference in the recession profiles between the top and bottom parts of the sample is neglected for the scope of this work, but requires further investigation to assess the degree of asymmetry.

3D temperature maps are shown for three representative time instants during the plasma exposure, providing temperature distributions over a large surface area of the ablated material surface. We also extract temperature profiles averaged around the azimuthal coordinate, where we highlight a 15% drop from the stagnation point value towards the sides and a steeper decrease as ablation occurs. This information can be used to study material ablation properties with further detail and to compare with multi-dimensional numerical simulations of the material response, thus overcoming traditional approaches that are limited around the stagnation region.

Additionally, the current technique can be extended to account for asymmetric ablation, provided that a suitable method is capable of tracking the surface in such conditions (e.g. photogrammetric techniques). Correction for temperature- and angular-dependent band emittance is also available in our model, thus extending the applicability to wider material classes.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Conflict of interest

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

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