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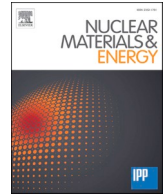
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Development of inverse methods for infrared thermography in fusion devices

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ABSTRACT

Infrared (IR) thermography system is a key diagnostic in fusion devices to monitor the Plasma Facing Components. Nevertheless, both qualitative and quantitative analysis (i.e. hot spot detection and surface temperature measurement) are challenging due to the presence of disturbance phenomena like variable emissivity and multiple reflections in fully metallic environment. Through the comparison with the experimental IR measurements, simulation is an essential tool for anticipating, quantifying and analysing the effects of the various errors involved in the interpretation of IR images. This paper goes a step further for achieving IR quantitative thermography in developing inverse methods to retrieve the real surface temperature, by taking into account variable emissivity and filtering reflections. Two approaches are studied: (1) using gradients methods through a reduced photonic model (2) using machine learning techniques based on simulated dataset. Applied on WEST-like tokamak numerical prototype, the temperatures are estimated, with these two approaches, with an accuracy better than 6%, which is a clear improvement compared to usual methods (i.e. assuming blackbody object).

1. Introduction

In magnetic fusion devices, the surface temperature measurement of plasma facing components is a major issue for both machine protection and plasma-wall interaction studies. Infrared (IR) imaging systems are then widely used in current fusion devices: this non-contact and non-destructive method allows monitoring almost all in-vessel components (e.g. 80% of ITER chamber) thanks to a network of cameras and this, on a wide temperature range (e.g. 200–3600 °C for ITER IR diagnostics). Nevertheless, temperature measurement is not direct from IR camera and the interpretation of IR images is especially complicated in tokamak, made up of fully radiative and reflective surfaces. In addition to the presence of multiple reflections adding parasitic signals, we must handle variable emissivity of targets as the operation progresses. This topic is still evolving since there is no yet a robust and reliable technique able to deal with both the variable emissivity and the presence of reflections.

Synthetic diagnostic is quite developed in the fusion community in order to predict the optical measurement in such a complex environment

[1–3]. A first evaluation of the performances of measurements from IR diagnostic for future ITER devices was carried out in [4] using a Monte Carlo ray tracing code. It proved that unknown emissivity can cause to underestimation of high temperature up to 40%, with a risk of not detecting hot spot and reflections leads an overestimation of coldest temperature impacting the measurement of plasma parameters (as plasma decay length). In [5], IR synthetic diagnostic was used for qualitative analysis of experimental IR images of WEST and ASDEX-Upgrade tokamak and to help discriminating reflections features from real thermal events.

This paper presents new developments for achieving IR quantitative thermography in tokamaks, based on inverse processing using IR synthetic diagnostic, to retrieve the true surface temperature measurement by correcting variable emissivity and filtering out reflections. The section 2 deals with the choice of forward model to be used for inversion, which should be a compromise between fast and performant model. The section 3 and 4 describe two approaches for solving the inverse problem based on gradient minimisation and on machine learning techniques. The first results of these two approaches, applied on WEST divertor

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view, are presented as well as the next improvements planned.

2. The inverse processing

Inverse problem aims at recovering unknown parameters (temperature and/or emissivity) of a thermal scene from the measured IR images (in radiance unit). To solve the inverse problem of IR thermography, two ways are studied and proposed. Both are based on forward model able to simulate the measurement from the observed thermal scene.

2.1. The challenge of forward model

The forward model is a digital twin which aims to be a virtual replica of physical device and instrument, modelling all physical phenomenon involved in the infrared measurement chain: from the plasma source to camera. As illustrated in Fig. 1, the forward model is based on a photon transport model able to propagate the rays in a 3D geometrical model and compute the radiance collected by each pixel to reproduce the camera image. The radiative transfer model uses as input the results of three others physical models:

- (1) a thermal scene model able to provide the 3D temperature field $T(x,y,z)$ resulting from the heat flux loads onto plasma facing components (PFCs). The heat loads come mainly from conducted particles along magnetic field lines which can cause power flux deposits up to 10 MW.m^{-2} in steady-state and 20 MW.m^{-2} during slow transient event (up to 10 s) (corresponding to materials design limit) [6]. The 3D deposited heat flux on PFCs is computed from a field line ray tracing code based on optical approximations (parallel transport only) for a given theoretical or experimental magnetic equilibrium [7,8,9]. A second source comes from the plasma radiation. For taking into account the multi-reflection inside metallic devices that changes the distribution of radiative power deposition, a ray tracing code is used to get 3D absorbed flux [10].
- (2) a materials thermo-radiative model able to describe the photons-wall interactions. Several studies have been carried out and are ongoing in order to find emission and reflections models for PFCs based on experimental measurements. In [11], in-situ emissivity measurement were performed on the WEST tokamak: complex emissivity distribution is observed on the divertor with a sharp spatial evolution of the emissivity from 0.05 to 0.85 at the monoblock scale ($\sim 12 \times 24 \text{ mm}$). This emissivity pattern is quite

coherent with the device configuration (in correlation with strike-point location and ripple modulation) and this can be implemented in the simulations as initial conditions and adjusted as the plasma operation progresses. Dedicated laboratory experiments were also performed to describe the angular dependency of material properties. It has been found that cosines n-power model is quite relevant to describe the angular dependency of materials emissivity [5]. Measurements on tungsten samples from goniometer have shown that reflections model fits the glossy surface model characterized by a narrow Gaussian lobe around the specular direction surface [12].

- (3) an optical model able to reproduce the camera view (field-of-view, pixel resolution) and taking into account the optical effects as distortions, diffractions and aberrations phenomenon.

The last point is the choice of photon transport model which requires a trade-off between the required accuracy, the computation time, and the 3D geometry. The choice of photon transport model is the key issue of inverse problem. Monte Carlo method is a very powerful tool to simulate photon transport and is quite widespread in the inverse rendering community. This allows dealing with complex 3D geometry and extensive models of photon-matter interactions [5]. Nevertheless, this is a statistical method which requires high computing time to achieve the needed accuracy. Then, in [13,14], an alternative numerical model of photons transport, based on radiosity transfer equation, has been developed. This is a fast model able to simulate IR images in a few seconds when view factors have been calculated beforehand (once) but introducing approximations on geometry and surface properties. Indeed, a strong assumption of this approach remains the diffuse behaviour of surface. Yet, by considering these two approaches, the one based on Monte Carlo method, performant but requiring high computing time, and the other based on radiosity method, fast but with approximations, the inversion problem will be dealt differently and two approaches have been developed. The first approach is based on classical optimization methods using the forward model in an iterative minimization loop (section 3). The second approach is based on machine learning techniques trained on a database of simulated images (section 4).

2.2. The particular case of thermal scene within tokamak

If thermal scenes in tokamaks are complex to solve because of the number of parameters to be estimated (which can be as high as 1 million

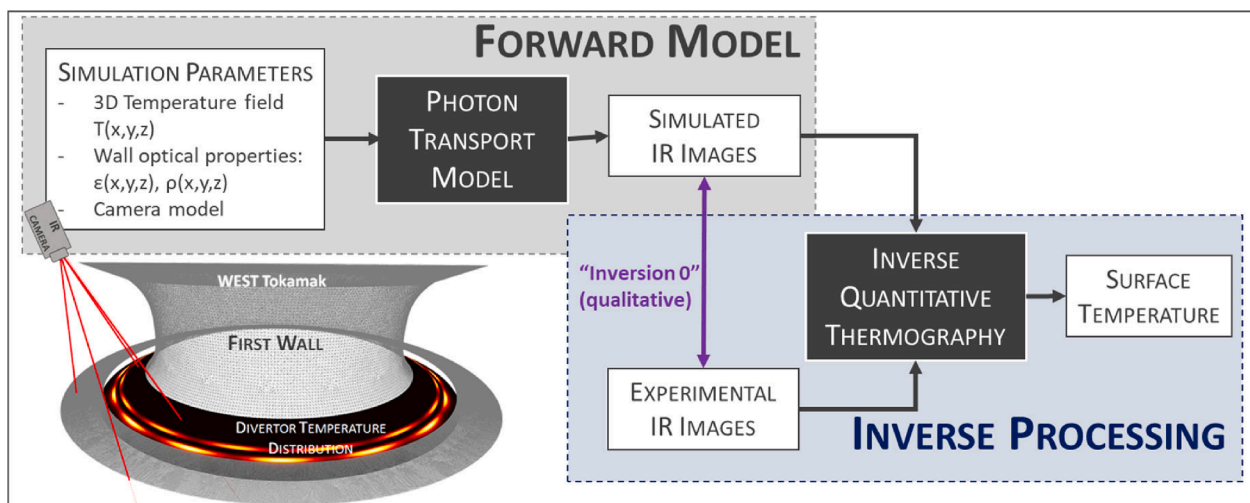


Fig. 1. Flow chart illustrating the link between the forward model and the inverse processing: the forward model provides simulated infrared images (in radiance units) for different thermal scenes, the inverse processing uses these simulated images to recover the surface temperature from IR experimental images.

if we consider all elements of 3D geometry and without any assumption of uniformity or known values), we can rely on the variety of scenario to decouple the estimation of temperature and emissivity. To estimate emissivity separately from temperature, we then propose to use the thermal scene during the conditioning phase or between pulse for which the temperature is globally uniform on the main components and quite well known (thanks in particular to embedded diagnostics as thermocouple). This reduces the number of parameters to be estimated but also the risk of existence of multiple solutions when estimating temperature and emissivity simultaneously (ill-posed problem). This implies such calibration phases must be done routinely in order to follow the materials' surface state and so emissivity change.

3. Gradient-based inversion of a thermal scene with diffuse reflective surfaces

3.1. Methodology

This first approach seeks to find the 3D temperature and/or emissivity fields in the thermal scene that are responsible for the measured 2D infrared image of this scene. The resolution of this inverse problem consists in minimizing a cost function that computes the difference between the experimental and simulated data (infrared images). The solution is then calculated by iterative updating of model parameters (temperature and/or emissivity fields) using a gradient optimization method [13,14]. The two key points in this approach are (1) the choice of photon transport model that is called in each loop and (2) the optimization algorithm for a fast convergence to the solution. For the first point, we turned to a fast photon transport model based on radiosity equations, able to generate an image in a few seconds, under assumption of diffuse surfaces in emission and reflection. For handling complex geometry, reduced radiative model based on hierarchical method has been developed, which consists in building multiresolution mesh as illustrated in Fig. 2(a). The geometry resolution is refined if the radiative exchange of the region of interest (3D-RoI) with the rest of the scene are significant whereas a rough mesh is kept on the elements whose radiative exchange with the 3D-RoI are low [15]. The 3D-RoI includes 3D

surfaces in a toroidal sector of 20° and a radial length of about 380 mm (see the 3D-RoI projected in white in the 2D-image of Fig. 2(a)). Regarding the second point, the minimization method will not be the same for the estimation of temperature and emissivity and their estimation will be done separately. Indeed, the estimation emissivity is a non-linear problem requiring iterative resolution. However, we proved in [12,13] that the temperature estimation can be reduced to a linear inverse problem and can be solved in an explicit way, without iteration, with the following matrix inversion:

$$L^o = (S^T S)^{-1} S^T Y_{inW}/m^2 sr \quad (1)$$

where L^o is the estimated black emitted radiance vector (size $p = 1,400$, the number of parameters) from which the target surface temperature is deduced, Y the vector of experimental measurement (radiance collected by each pixel, size $m = 49,500$ pixels), S the sensitivity (Jacobian) matrix of the model output for the estimated parameters (black emitted radiance L^o) of $[m \times p]$ size. The S matrix depends on emissivity but not on temperature and is built with p calls to the forward model [13]. The main advantage of such a method is that the inverse operator $(S^T S)^{-1} S^T$ needs to be computed only once if emissivity is known. The main limitation is the large size $[p \times m]$ of this inverse operator which leads to restricting the numbers of parameters to be found (thanks to a priori expectations on given values or spatial profiles) and/or the number of measurements (pixels) by solving only a part of image.

3.2. Results on WEST numerical prototype

Such a method has been tested on numerical prototype based on WEST simple geometry. In this first demonstration, we focus on IR camera view looking at WEST divertor, which is less sensitive to reflection contribution but more demanding on temperature measurement accuracy for physics study. Furthermore, the IR spatial resolution of such a view (2–3 mm/pixel) is good enough and, in this case, the resulting error is much less significant compared to others contributors as emissivity uncertainties and reflections contributions. Uniform emissivity is assumed for all in-vessel components (fixed at 0.1 for upper

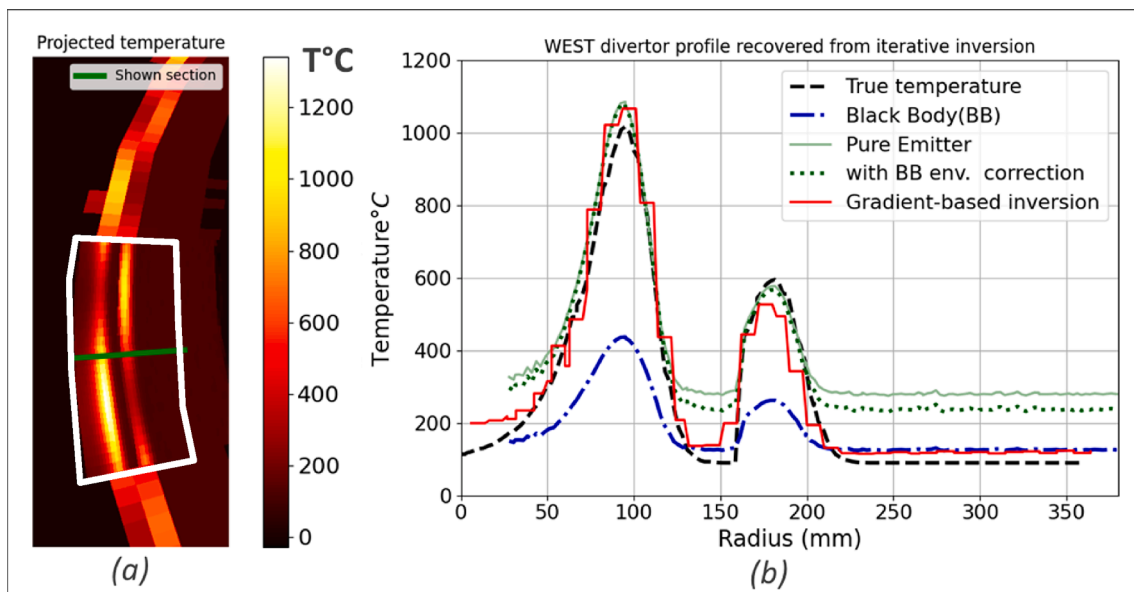


Fig. 2. (a) Projected true temperatures of WEST standard camera providing a top view of lower divertor. Image is the result of 3D-2D mapping of solution computed from gradient-based inversion. Image multiresolution is the result of reduced radiative transfer model using adaptive meshing. The white region shows the pixels corresponding to the 3D-RoI (b) Simulated temperature profiles on lower divertor extracted from IR simulated images. The estimated temperature from gradient-based inversion (red curve) is compared to the true temperature profile used as input of simulation (black curve) and the temperature deduced from IR images using usual methods (blue and green curves). The x-axis is actually the pixel number along the green line in (a) translated in radius (mm) in the 3D world thanks to a preliminary 3D → 2D pixel size calibration.

and lower divertor and baffle and 0.3 for first wall). Uniform temperature (fixed at 90 °C) is assumed for the main plasma facing components (baffle, upper divertor, first wall) except for the lower divertor, receiving the highest heat loads. We are interested in recovering the temperature profile on WEST divertor from experimental-like IR image generated using Monte Carlo Ray Tracing code (image noise inherent to the stochastic methods). To estimate the temperature, the emissivity profile is known and previously computed using iterative resolution from uniform thermal scene, e.g. during the conditioning phase [13]. It is worth noting that no a priori temperature profile is assumed for inner and outer W surfaces of lower divertor inside the 3D-RoI, but this pattern is assumed periodically repeated in the toroidal direction for the whole divertor. Temperature of surrounding components (baffle, first wall, upper divertor) is assumed to be known (at 90 °C), which reduces the number of parameters to be estimated to 1,390 (measurement vector Y in equation (1) is then modified to include the known parameters [13]). It is worth reminding that in this approach, the temperature is directly estimated on the elements of 3D geometry (and not on pixels of IR images) which also allows to take into account errors coming from the camera resolution. Fig. 2(a) shows the mapping of 3D solution to 2D image, only for display purposes and for comparison with other calculated temperatures resulting from classical 2D image processings shown on Fig. 2(b) : (1) the apparent temperature equivalent to a blackbody of emissivity 1, without correction of additional reflected flux (2) the apparent temperature so-called pure emitter assuming the target emissivity known but without correction of reflected flux (3) the apparent temperature so-called “black environment” assuming known emissivity and with a simple correction of reflected flux considering the radiative environment acting as blackbody of known temperature. The measurement error is the discrepancy between the true surface temperature used as input of simulation and the resulting temperatures from IR simulated images. In the case of diffuse surface, the gradient-based inversion can estimate the temperature with an accuracy better than 30% on the coldest target and better than 6% on peak temperature.

4. Neural network inversion of a thermal scene with specular reflective surfaces

The second approach is based on deep learning techniques. This technique works on images and aims to provide the 2D images of real temperature and emissivity that correspond to the measured 2D infrared image of the 3D thermal scene. The technique relies on training a convolutional neural network (CNN) on a synthetic dataset. The first challenge is to construct a representative and large dataset [16]. For this first demonstration, a deterministic ray tracing, applicable only to purely specular materials (mirror type) was developed to generate quickly IR images and build a database of 15,000 images [17]. The method has been tested on WEST geometry. A uniform temperature is assumed between 300 °C and 500 °C for the WEST components close to plasma (e.g. bumper, antenna outboard) and between 90° and 110 °C for the rest of components (baffle, first wall, upper divertor, non facing plasma components). Only a non-uniform temperature is applied on the lower divertor. It is worth noting that for this first demonstration applied only on simulated data, we did not use field line ray tracing, as mentioned in section 1, to establish the temperature distribution on divertor: we used analytical formulae inspired to Eich formulae [18] to roughly reproduce quickly the heat loads in a tokamak with two strike points and a toroidal modulation of a 20° period to reproduce the ripple effect. Lambertian emission (i.e. with no angular dependency) and uniform emissivity, with a variable value between 0.05 and 0.5, is also assumed for all components. The dataset is built by changing 77 parameters of forward model (emissivity and temperature values of the 36 in-vessel components, emissivity and 4 parameters of “Eich formulae” describing the divertor temperature distribution).

Latin hypercube sampling algorithms were then used to optimally cover the range of parameters and generate representative training

dataset of different plasma scenarios. For training the model using this dataset, a deep fully convolutional neural network, inspired from the original U-Net architecture, has been implemented. Unlike classical CNN used to encode and decode image as a class label, the U-net is particularly suitable for classifying each pixel of images and thus dealing with images both as input and output. The network is trained with a triplet of images including the camera image (in radiance unit) and the associated real temperature and emissivity maps. Fig. 3 shows the WEST temperature radial profile on the lower divertor extracted from simulated IR images after applying usual methods and neural network (NN) inversion. Here again, the first results obtained are encouraging: contrary to classical methods (considering blackbody object, pure emitter or with simple correction of reflected flux), high specular patterns are quite removed with NN inversion. On a base of 5000 test images (generated without additional noise), temperature errors are found to be lower than 6 %. The absolute emissivity errors are lower than 0.005 on the divertor region. It should be noted that with this approach, the scene temperatures and emissivities are found simultaneously. The very good results are most likely made possible by the purely specular behavior of the materials which will generate very different images when the thermal scene parameters change.

5. Conclusion

Inverse methods are being investigated to solve reflections and variable emissivity issues in infrared images within fusion devices. Two different approaches are being developed. The first one is a gradient inversion using a reduced photonic model based on radiosity equations. Such an approach is valid only in the case where all surfaces are diffuse. No prior distribution of temperature on the divertor is assumed, except the repeated toroidal pattern with a period of 20°. The second approach is based on machine learning techniques and consists in training a neural network from a simulated dataset. In order to quickly get a wide training dataset, two choices have been made : (1) a fast deterministic ray tracing has been developed in the case where all surfaces have specular reflectance (acting as mirror) and lambertian emission and (2) a prior non-uniform temperature distribution based on “Eich formulae” has been assumed for the divertor as well as uniform temperature and emissivity for the rest of components. Only 77 parameters are then used to describe the full thermal scene in the tokamak and to reproduce realistic situations. This parameters number could be increased to extent the scenario learnt by neural network. For these two “extreme” cases (diffuse and specular surfaces in reflection), the first results obtained with the two approaches are promising with a significant improvement of surface temperature measurement accuracy compared to usual techniques of image processing (considering blackbody object, pure emitter or with simple correction of contribution of radiative environment). This encourages us to pursue the two approaches to solve real surface with complex bidirectional reflectance distribution function combining diffuse and glossy (Gaussian specular) components. This involves developing more complex model based on radiosity or accelerating the computing time of ray tracing code for getting large training dataset. Another step is to integrate more complex thermal conditions like transient events. A next step is to demonstrate the limits of validity of the two approaches on controlled experiences in laboratory (by adding complexity progressively), before testing on tokamaks in operation.

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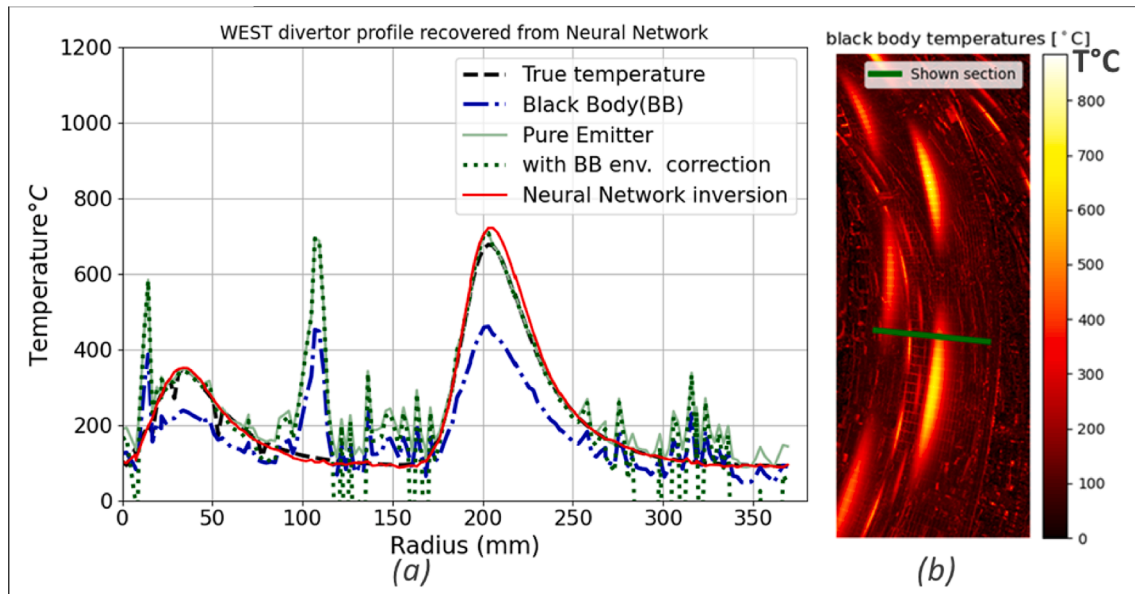


Fig. 3. (a) Temperature profile on WEST divertor extracted from IR simulated images (generated without additional noise). Contrary to gradient-based inversion, the solution is here computed on pixels, and not on 3D elements; the x-axis is actually the pixel number along the green line in (b) translated in radius (mm) in the 3D world thanks to a preliminar 3D → 2D pixel size calibration. The estimated temperature from neural network inversion (red curve) is compared to the true temperature profile used as input of simulation (black curve) and the temperature deduced from IR simulated images using usual methods (blue and green curves) (b) Simulated apparent temperature maps for the case of all specular surface (mirror): here black body temperatures are shown instead of true temperatures in order to show the artefacts due to wrong interpretation of reflections (c) True temperature used as input of photonic simulation projected on 2D maps.

CRedit authorship contribution statement

M.-H. Aumeunier: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **M. Le Bohec:** Formal analysis, Software, Writing – review & editing. **R. Brunet:** Formal analysis, Software, Writing – review & editing. **A. Juven:** Formal analysis, Software, Writing – review & editing. **M. Adel:** Supervision, Writing – review & editing. **X. Artusi:** Writing – review & editing. **R. Miorelli:** Investigation, Writing – review & editing. **C. Reboud:** Supervision, Writing – review & editing. **F. Rigollet:** Investigation, Writing – review & editing.

Declaration of Competing 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.

Data availability

Data will be made available on request.

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