



**HAL**  
open science

## **Infrared measurement synthetic database for inverse thermography model based on deep learning**

R. Brunet, M-H. Aumeunier, R. Miorelli, A. Juven, Christophe Reboud,  
Xavier Artusi, M. Le Bohec

► **To cite this version:**

R. Brunet, M-H. Aumeunier, R. Miorelli, A. Juven, Christophe Reboud, et al.. Infrared measurement synthetic database for inverse thermography model based on deep learning. *Fusion Engineering and Design*, 2023, 192, pp.113598. 10.1016/j.fusengdes.2023.113598 . cea-04077532

**HAL Id: cea-04077532**

**<https://cea.hal.science/cea-04077532>**

Submitted on 30 Aug 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Infrared measurement synthetic database for inverse thermography model based on deep learning

R. Brunet<sup>1\*</sup>, M-H. Aumeunier<sup>1</sup>, R. Miorelli<sup>2</sup>, A. Juven<sup>1</sup>, C. Reboud<sup>2</sup>, X. Artusi<sup>2</sup>, M. Le Bohec<sup>1</sup>

<sup>1</sup>CEA, IRFM, F-13108 Saint-Paul-lez-Durance, France

<sup>2</sup>Université Paris-Saclay, CEA, List, F-91120, Palaiseau, France

**Infrared (IR) diagnostics are used to measure the surface temperature of plasma-facing components in fusion devices. However, the interpretation of such images and any quantitative analysis are very complex in all-reflective environments because of unknown emissivity and multiple reflections. This is an important issue for safe operation and understanding of plasma-wall interaction phenomena. Moreover, it can also benefit other industrial applications e.g., monitor heating on production lines, additive manufacturing devices, etc. Recently, a first demonstration of simulation-assisted machine learning method has proven to be effective in retrieving surface temperatures from IR measurements. Yet, the performances of such an approach has been evaluated on a tokamak prototype considering pure specular surfaces. This paper presents an optimised generation of training dataset based on a synthetic data generated by a deterministic ray tracer model. The obtained results shows that the proposed methodology enables very accurate simulations minimizing the computational burden associate to greedy models (i.e., Monte Carlo type) to generate training data for realistic surfaces.**

*Keywords:* infrared, thermography, machine learning, inverse problem, optimisation

## 1. Introduction

Infrared (IR) thermography system is a key diagnostic in fusion devices to monitor the Plasma Facing Components (PFC). However, obtain reliable surface temperatures of metallic PFCs directly from infrared images is challenging. Indeed, in a fully metallic and reflective environment, IR interpretation is disturbed by the low and variable emissivities of targets. Parasitic flux coming from reflections of a hot environment may cause important measurement errors from little percentage up to 100 percent in cold regions [1]. Such errors are critical for machine operations with risks of component damage due to underestimated temperature or false alarms limiting the plasma performances due to temperature overestimation. Therefore, our objective is to develop a robust and efficient numerical inverse method for estimating temperatures from IR images.

Toward this end, our forward model is based on an efficient synthetic diagnostics (so called digital twin) [2], able to simulate accurately IR images from a thermal scene in a tokamak, including multiple reflections and non-uniform emissivities. In [3], a first inverse model has been implemented based on a deep-learning neural network trained on a simulated dataset, using fast ray tracer and assuming specular surfaces (acting as mirror). The obtained results showed that surface temperature can be found with an accuracy better than 5 percent. The main challenge is on the extension of such a method to more plasma scenarios, including complex optical properties of materials (i.e. diffuse, glossy surfaces). That is, simulating complex thermal scenes with a high fidelity level requires high computing time. Typically, classical Monte Carlo Ray Tracing code (MCRT), able to handle such complexity, requires 12 hours per images with 4-core CPU. The difficulty is then to get an optimised training dataset aiming at minimizing the number of simulated images by selecting the most representative of tokamak experiments. In this paper, we propose an adaptive sampling strategy for constructing optimised training synthetic IR dataset. The section 2 and 3 present the adaptive sampling strategy implemented for IR images in tokamak, based on Principal Component Analysis (PCA). In section 4, the performances of the proposed method are evaluated by comparing the results obtained from a reference huge training dataset (of 5 000 simulated images) and the ones coming from an optimised training dataset after adaptive sampling.

## 2. Adaptive sampling

The idea and the point of adaptive sampling is, in the first place, to cover the wider range of inputs as possible, while limiting the number of samples. The first step is the input parameters' reduction. Indeed, an important number of parameters, used as input of IR synthetic diagnostic, are required to describe a complex thermal scene in tokamak.

Typically, each point of the 3D thermal scene wall should be characterised by 5 to 8 physical parameters: temperature and normal emissivity values, parameters of model of angular-dependence of emissivity, parameters of Bidirectional Reflectance Distribution Function (BRDF). Since we are dealing with finely meshed geometries to be sure to capture all the potential reflections, this would lead to take into account several millions of input parameters (i.e. 2 millions of nodes x number of physical parameters). In a first approximation, for the results presented in this paper, the number of inputs parameters has been drastically reduced, assuming uniform temperature and material properties for all the geometries and PFCs, except the lower divertor. For the lower divertor we use the parameterised so-called Eich formulae to mimic the temperature patterns. We end up with 49 input parameters, temperature and emissivity (material property in our case of purely specular surfaces) for 22 components, to which we add the emissivity and Eich formulae (4 parameters) for the lower divertor. The number of parameters would be increased for more complex parametrisation of the tokamak scene.

The second step is to get a first distribution of input parameters in a given range and equitably distributed. To do that, we use the Latin Hypercube Sampling (LHS), which is a statistical method ensuring that all inputs are the furthest apart dimension wise. The new method, proposed in this paper, will aim at obtaining a better distribution of input parameters in the sense that it will represent a wider variety of outputs, and so improves the accuracy of our inverse model based on the optimised training dataset.

Unlike the usual training set sampling strategies whose goal is to fill homogeneously the input spaces, we propose a sampling strategy relying on sampling the space spanned by the outputs [4]. We refer to this space as extracted feature space. The latter is computed by applying the PCA [5] algorithm to our entire initialisation set of IR images projected into the latent space spanned by the principal components. That is, the PCA extracts a suitable subspace from the given set of inputs (IR images in our case) having a smaller (or much smaller) dimension compared to the IR images. The projection of those inputs on this subspace maximises the variance of the whole dataset, meaning capturing a maximum of information from it. Therefore, a homogeneous fill of the space spanned by the principal components corresponds in capturing the maximum variance of all the signals associated to the considered problem. Furthermore, by projecting the database into this latent space, we can analyse and extract information from the whole set. For instance, we can monitor the impacts of our problem's input parameters on the corresponding outputs (IR images). We then fill those extracted feature spaces through our algorithm, referred as the Feature Space Filling (FSF) algorithm [6], at locations where we considered, via a metric we set, there is missing information which could help later on our inverse model ("improving" the dataset). The number of latent components (dimensions of subspace) can be conveniently chosen by considering the cumulative sum of the so-called explained variance that represents how much variation in a dataset can be attributed to each of the principal components generated by the method.

### 3. Filling strategy

Figure 1 is a way to represent the spatial distribution of input parameters of simulations, and therefore the consequence of this method. We show here temperature of outer divertor as a function of emissivity of lower divertor. Classical algorithm (LHS) (orange points) gives uniform distribution along each axis, without considering the sensitivity of input parameters on the of simulation. On the contrary, PCA analysis (blue points) will increase the sampling around the input parameters the most sensitive (with higher gradient on the outputs).

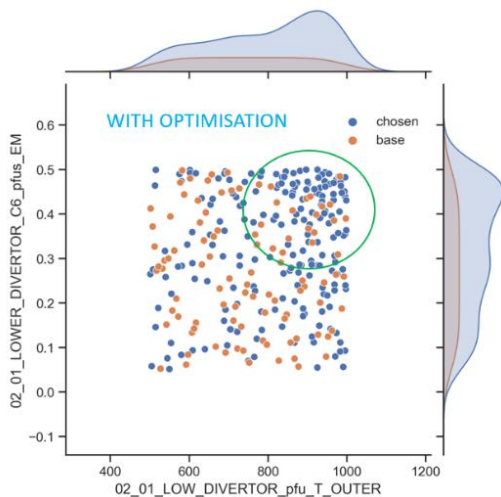


Figure 1: The inputs corresponds to the emissivity (range is from 0.05 to 0.5) and surface temperature (range is from 600 to 1200) of the lower divertor. For classical algorithm (LHS), in orange points), one can see it is equally distributed (orange curves along up and right axis). As for the optimised method, they tend to cluster at the top right corner of the image, meaning the best distribution in terms of impact in the output space does not mean parameters equidistant in the input spaces.

identifying the most influent parameters. In a first step, PCAs (linear method) has been implemented since it is very efficient for compensating Monte Carlo statistical noise. Non-linear method is also considered and will be compared later.

The second step consists in increasing this initial dataset to another 200 images. To do that, two preliminary steps are needed. Firstly, we compute a so-called global tolerance within these projected initial dataset latent space values, which measures how "different" those images are from each other, meaning how much they represent diverse physical scenarios. It is used when a potential newcomer is projected in the feature space to establish if it is "sufficiently far" from the features of the rest of the samples or not. It can be translated as a scalar giving a one-dimension minimum distance value, which will be compared with any candidate for each dimension.

Secondly, this initial training dataset is used to train a neural network, establishing the relation between input parameters and principal components. This meta-model tells us where a potentially new computed scenario would be projected if we run it through the digital twin, saving us the computing time of a forward model's pass which could be very costly.

When these two steps are performed, the training dataset can be completed in an optimised way. To do that, we test number of candidates given by a LHS sampling. In our present case, the number of candidates must around 500, not too small to be sure we have enough good candidates per round. After a first slice of the candidates with the global tolerance previously computed, which takes us from 500 to about 50 to 150 suitable candidates. It is worth noticing that each time a candidate is judged as suitable, the dataset is updated in order to compare the following candidates with the latter, a second slice is made taking the 10 suitable samples whose minimum distance dimension wise are the biggest.

After the new samples have been chosen, we update the global tolerance and the meta-model until the loop is over. The loop stops when the predefined number of samples (300 in our case) has been reached.

The final step is to evaluate the performances of a NN based inverse model when trained on the "optimised" dataset and comparing it with a NN trained on a non-optimised (naïve) dataset of 300 images (meaning directly generated from a LHS of size 300 and without PCA analysis). We assess the performance of the NNs on a test set made of 5 000 images.

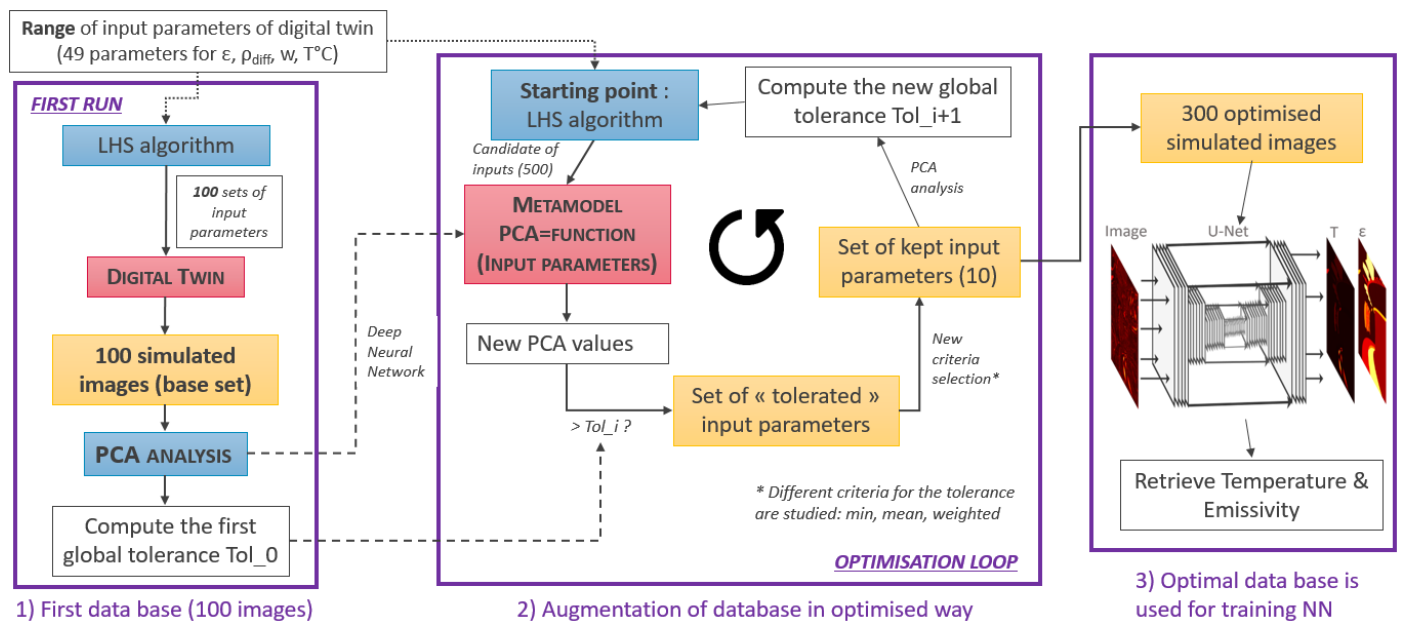


Figure 2: Workflow diagram of filling strategy: (1) Construction of the initial dataset from which the first meta-model and global tolerance are derived (2) the filling loop to increase the dataset with the resulting updates (3) the optimal database is used to train the deep learning based inverse model.

#### 4. Results

To assess the performances of adaptive sampling on machine learning techniques, we base this on the work performed in [3] using supervised deep learning (U-Net) to establish inverse model able to find the surface temperature and emissivity maps from an infrared image. These results have been obtained from a fast radiative model, so-called Speculos that is a "deterministic" ray tracer able to propagate rays in 3D meshed geometry considering pure specular surfaces (i.e., acting as mirror). This allows generating a large database quickly and testing methods feasibility. For this purpose, the thermal scene (1 million meshes geometry) is described by 49 parameters. Emissivities are between 0.05 and 0.5 for all components, temperatures are between 80 °C and 120 °C for the first wall, higher temperatures from 300 °C to 500 °C is assumed for components close to the plasma, and the maximum temperature of divertor

temperature profile can rise to 1800 °C. We compare two synthetic datasets: (1) a “naïve” dataset generated from simple LHS sampling and (2) an optimised dataset using adaptive sampling strategy proposed. We make three databases of each kind, starting from 100 images and reaching 300 images, and for each one of them, we have done 10 trainings on our deep-learning based inverse model, using 20% of the total dataset as our validation set. The performances of neural networks trained by the two kinds of dataset are then assessed from a set of 2000 images. Our criterion to determine the good number of images required is based on the ITER specifications (i.e. 10% error for high temperature >400°C and 20% for lower temperature)

The mean relative error from temperature on all geometries except divertor is of 8% for optimised method and 13% for naïve method, whereas on the divertor, it goes from 9% for our method as shown in Figure 3, up to 15% for the “naïve” one. The main problem for this latter method which appeared, is that it regularly misses the divertor pattern. Figure 4 shows the temperature profile on lower divertor extracted from one synthetic image: the true temperature of targets used as input of photonic simulation is compared to temperature found from IR image using machine learning. We compare here the temperature predicted by 3 different NN trained with naïve dataset of 300 images, with optimised dataset of 250 and 300 images. Predicted temperatures are also compared to the apparent temperature (or blackbody temperature assuming emissivity equal to 1 without any correction). The NN trained with naïve dataset does not allow finding the temperature profile. It is shown that 250 images for training dataset is not sufficient, even after optimization. In this case, the predicted temperature error is equivalent to the BB temperature. However, very good results have been obtained with NN trained with optimised dataset of 300 images with an error lower than 5%.

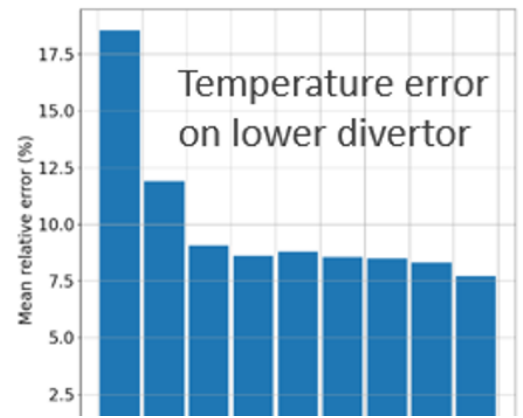
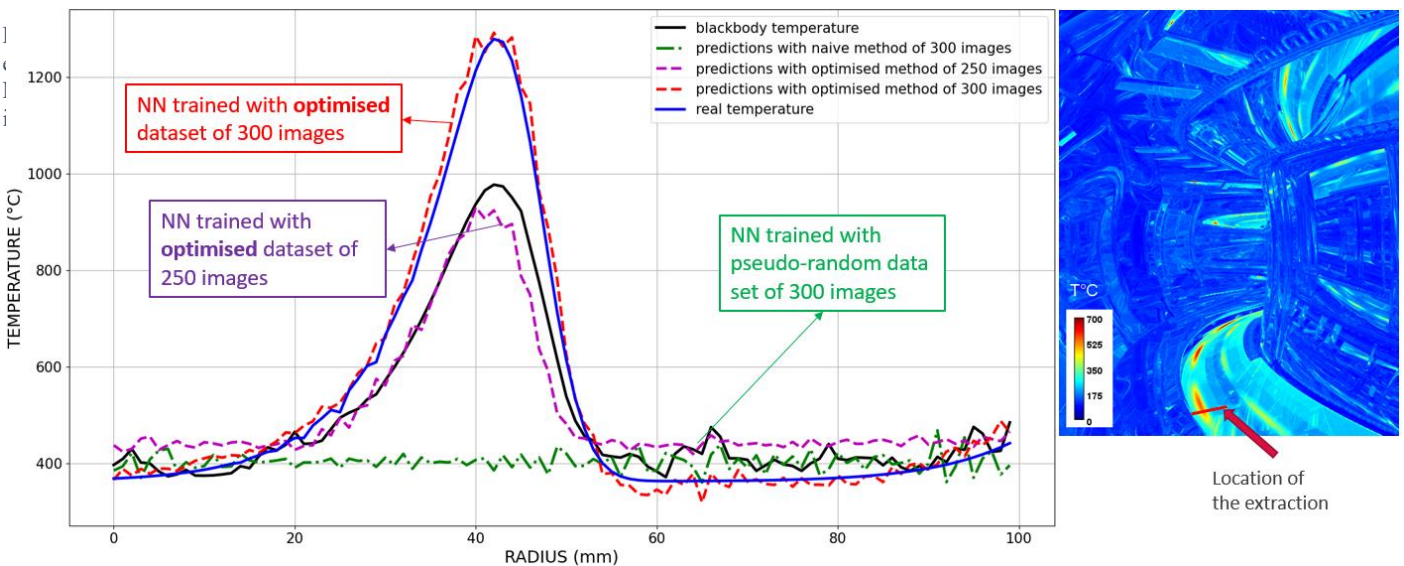


Figure 3: Testing set mean relative error percentage on the lower divertor estimation per temperature range after an adaptive sampling. Error being higher for lower temperatures since it is when we face more reflections, and therefore more difficulty to approximate.



## 5. Conclusion and outlooks

IR inverse thermography using simulated data coupled to machine learning techniques is a promising approach but the challenge is to get reliable and unbiased training data set of simulated images while keeping reasonable computing time. Adaptive sampling method based on PCA analysis gives encouraging results to downsize the training data set from 15 000 to 300 images with similar performances, which translates into a time saving (with CPU ray tracer on 4-core), of  $(15000-300)*30min = 300$  days. These first results have been obtained for idealistic cases assuming pure specular surface and uniform temperature except for divertor.

The next step will be to extend the method on real condition of tokamak with complex thermal scenes (especially including real surface properties and local hot spots). The adaptive sampling is an important method to deal with the very large number of potential thermal scene in tokamaks. Such a method allows us to keep highly accurate simulations from methods greedy in computing time, such as ray tracer methods (Monte Carlo type), but also for any heavy physical codes, keeping the goal of generate quickly training datasets specific for NN. In our case, it enables high accuracy in terms of NN predictions for the estimation of surface temperature from infrared images.

## Acknowledgements

*We acknowledge the financial support of the Cross-Disciplinary Program on Numerical Simulation of CEA, the French Alternative Energies and Atomic Energy Commission.*

*This work has been carried out within the framework of the EUROfusion Consortium, funded by the European Union via the Euratom Research and Training Programme (Grant Agreement No 101052200 — EUROfusion). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.*

## References

- [1] Aumeunier M-H. et al., “Simulation of the Infrared Views of the Upper Port VIS/IR Imaging System of ITER” , Nuclear Materials and Energy 12 (2017) 1265–1269
- [2] M-H Aumeunier et al., Nuclear Materials and Energy 26 (2021) 100879
- [3] A. Juven et al., Temperature estimation in fusion devices using machine learning techniques on infrared specular synthetic data, in: IEEE 14th Image Video, and Multidimensional Signal Processing Workshop (IVMSP), 2022, pp. 1–5
- [4] R. Miorelli et al., An efficient adaptive database sampling strategy with applications to eddy current signals, Simulation Modelling Practice and Theory, 2018
- [5] Jolliffe, I.T., Principal component analysis. Springer Series in Statistics, Springer-Verlang, New York (1986)
- [6] R. Miorelli et al., Flaw characterization in conductive media based on pulsed Eddy current measurements: A fast non-iterative inversion approach, IET Science, Measurement & Technology, 2021