QIRT'2022

10.21611/qirt.2022.3040

16th Quantitative InfraRed Thermography Conference

Temperature measurements of opaque materials at high temperatures using multi-spectral methods

by K. Ennass*(1,2,3), B. Remy(1,2), V. Schick(1,2) and J.Meulemans(2,3)

[1] Laboratoire Énergies et Mécanique Théorique et Appliquée, Université de Lorraine, CNRS, 2 Av. de la Forêt de Haye, 54500 Vandœuvre-lès-Nancy, France
[2] Laboratoire commun Canopée, CNRS, Université de Lorraine, Saint-Gobain
[3] Saint-Gobain Research Paris, 39 quai Lucien Lefranc, F-93303 Aubervilliers, France
*(auteur correspondant : kamal.ennass@saint-gobain.com)

Abstract:

Precise and accurate temperature measurements during material manufacturing processes are crucial for obtaining the desired properties. In the context of this study, the metrological tool used for the measurements will be the multi-spectral infrared thermography. This non-intrusive tool is coupled with the Particle Swarm Optimization algorithm (PSO algorithm) for the simultaneous estimation of temperature and spectral emissivity variations in the case of opaque bodies by using an analytical model based on finite elements parametrization.

1. Introduction:

Temperature measurements are subject to disturbances due to numerous measurement biases and experimental noises. Reliable and robust high temperature measurements are essential for piloting industrial processes more finely and to reduce their energy consumption.

In this work, the preferred metrological tool is multi-spectral infrared thermography, a non-contact measurement method.

There are several previous studies carried out on the non-contact measurement of surface temperature, we can cite in particular broadband pyrometry, monochromatic pyrometry, bichromatic pyrometry (Krapez 2011 [1]), polychromatic (or multi-spectral) pyrometry (Araujo 2017 [2]; Coates 1981 [3]; Duvaut 1995 [4]; Gardner 1981 [5]). The biases of multi-spectral methods (Krapez 2019 [6]) and optimal wavelengths for estimation (Rodiet 2014 [7]) have also been documented.

In this paper, we particularly focus our attention on the effect of bias model for describing the spectral emissivity that leads to systematic errors on estimated values of unknown parameters.

2. Methodology:

A major challenge for temperature estimation is the lack of knowledge of the optical properties of opaque materials and their evolution as a function of temperature, wavelength and time, which can deteriorate the accuracy of the estimation.

To avoid this problem, a multi-spectral method has been developed to estimate simultaneously the spectral emissivity and temperature by using the following analytical expression of the radiative heat flux based on finite elements formulation using P1 elements:

$$\varphi(\lambda_i, T) = \left(\sum_{j=1}^{n} \varepsilon_{\lambda_j} N_j(\lambda)\right) . \frac{C_1 . \lambda_i^{-5}}{\exp\left(\frac{C_2}{\lambda_i . T}\right) - 1} \tag{1}$$

Where ε_{λ_j} is the spectral emissivity coefficient at λ_j, $N_j(\lambda)$ is the hat function, T is the temperature of the surface, λ_i is the wavelength and $C_1 = 2hc^2 \; W.m^2$ and $C_2 = \frac{hc}{k} \; m.K$ are the first and the second radiation constants, respectively.

By using this method, the so-called "piecewise" functions are able to describe in high accuracy several types of emissivity variations by continuous functions and derivatives. Another advantage is that the estimated parameters all have a physical meaning defined in a finite domain, unlike previously developed approaches [8], which allows us to use constrained optimization algorithms.

The following objective function is then minimized using a minimization algorithm such as Particle Swarm Optimization (PSO) [9], by using MATLAB's "particleswarm" toolbox, to find the optimal values of temperature and emissivity coefficients:

$$J(T, \varepsilon_1, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_n) = \sum_{i=1}^{n+1} (\varphi^{exp}(\lambda_i) - \varphi(\lambda_i, T, \varepsilon_1, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_n))^2 \qquad (2)$$

3. Results:

Monte Carlo simulations were carried out to evaluate the algorithm's robustness towards different initial points for unknown parameters. The figures below show the estimation errors for temperature versus the normalized norm of residuals $\frac{J}{(n+1)\varphi^{exp}}$ obtained with PSO for the estimation of two different levels of temperatures and seven coefficients of emissivity evenly distributed in the spectral band $[2\mu m, 4\mu m]$ using 8 wavelengths equally distanced in the same spectral band (the experimental heat flux is simulated). The "real" spectral emissivity is simulated using Drude's model (which is used for pure metals' emissivity [10]) varying between 1 and 0.6:

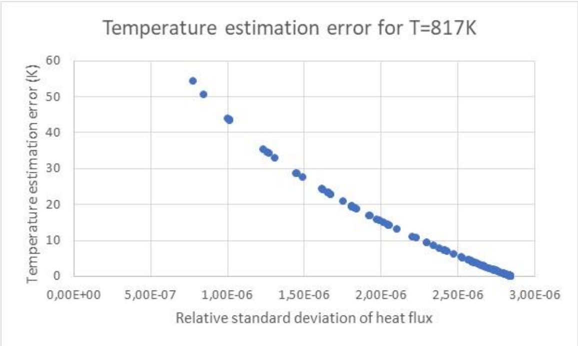

Fig. 1. *Estimation error for a true temperature of 817K*

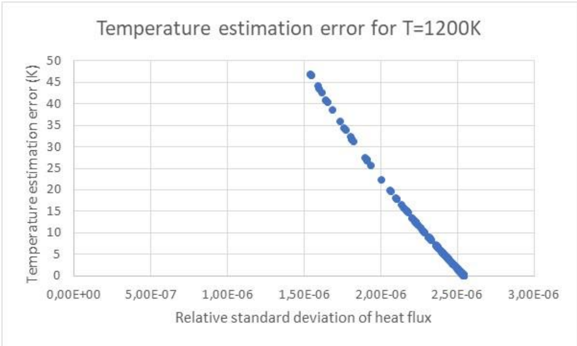

Fig. 2. *Estimation error for a true temperature of 1200K*

We observe that varying initial points results in a dispersion of estimation precision. Empirically, the highest accuracy can be obtained at the maximum relative standard deviation of heat flux or residuals due to the model's bias. The unbiased solution is obtained when the residuals curve is orthogonal with the biased model's sensitivity matrix. Below this value, the algorithm is capable of minimizing the objective function or residuals past it's optimal value by compensating the committed temperature error on the estimated emissivity coefficients. In this case, the estimated parameters are corrupted with a systematic error or bias. A theoretical explanation of this phenomena is currently being developed.

Experiments regarding emissivity measurements of real materials are also currently being carried out using a broadband InSb camera that allows measurements between $[1.5\mu m, 5.5\mu m]$, to be then used for validating simulation results.

REFERENCES

[1] Krapez, J.C. (2011). Radiative Measurements of Temperature. *Thermal Measurements and Inverse Techniques*, Heat Transfer. CRC Press, Boca Raton, FL. OCLC: ocn587104377.
[2] A. Araujo. Multi-spectral pyrometry - a review. *Measurement Science and Technology*, vol. 28, number 8, 2017.
[3] P.B. Coates. Multi-Wavelength Pyrometry. *Metrologia*, Volume 17, Number 3, 1981.
[4] F. Meriaudeau. Real time multispectral high temperature measurement: Application to control in the industry. *Image and Vision Computing*, vol. 25, issue 7, p. 1124-1133, 2007.
[5] Gardner, J. L.; Jones, T. P.; Davies, M. R. A six-wavelength radiation pyrometer. *High Temp. High Press*. 1981; 13:459-466. http://hdl.handle.net/102.100.100/290999?index=1.
[6] J.-C. Krapez. Measurements without contact in heat transfer: multiwavelength radiation thermometry. Principle, implementation and pitfalls. In: METTI 7 Advanced School: *Thermal Measurements and Inverse Techniques*, Porquerolles, France, 2019.
[7] Ch. Rodiet. *Temperature Measurement by Multi-Spectral Methods and Thermal Characterization of Anisotropic Materials by Integral Transforms: "Theoretical and experimental aspects*. Doctoral thesis, University of Lorraine, 2014.
[8] Ch. Rodiet & T. Pierre & B. Remy & Degiovanni, Alain. (2011). *Mesure de température par méthode multi-spectrale dans l'Infrarouge et l'Ultraviolet.* 10.13140/2.1.3136.7043.
[9] J. Kennedy and R. Eberhart. "Particle swarm optimization," Proceedings of ICNN'95 - *International Conference on Neural Networks*, 1995, pp. 1942-1948 vol.4, doi: 10.1109/ICNN.1995.488968.
[10] J. Taine and J.-P. PETIT. *Transferts thermiques*. Dunod, 2003.