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Sensitivity of different methods for simultaneous evaluation of emissivity and temperature through multispectral infrared thermography simulation

Thibaud TOULLIER[1,2], Jean DUMOULIN[2,1], Laurent MEVEL[1,2]
[1] *Inria, I4S Team, Campus de Beaulieu, 35042, Rennes, France*
[2] *IFSTTAR, COSYS-SII, Allée des Ponts et Chaussées, 44344, Bouguenais, France*
http://www.sii.ifsttar.fr/ & https://team.inria.fr/i4s/

Introduction and nomenclature

This study focuses on the simultaneous evaluation of temperature and emissivity with multispectral infrared thermography (IRT). It leans on the study and development of an IRT simulator able to address 3D scene in static or dynamic configuration. The sensitivity of 4 different temperature and emissivity joint estimation methods are then evaluated.

$\Delta\lambda_i$	Wavelength interval of i^{th} band	$B_{k,\Delta\lambda_i}$	Radiosity of patch k on $\Delta\lambda_i$
$\epsilon_{\mathrm{k},\Delta\lambda_i}$	Emissivity of patch k in $\Delta\lambda_i$	$M_{k,\Delta\lambda_i}$	Emittance of patch k on $\Delta\lambda_i$
T	Object's temperature	$V_{kj} = \{0,1\}$	Visibility between patches k and j

IRT Simulator through the radiosity method

View factor

Geometrical coefficient for radiative exchange between two diffuse elements

$$F_{1\to 2} = \int_{A_1}\int_{A_2} \frac{\cos(\theta_1)\cos(\theta_2)}{\pi r^2}\, dA_1 dA_2$$

Radiosity equation[1]

$$B_{k,\Delta\lambda_i} = M_{k,\Delta\lambda_i} + \left(1-\epsilon_{k,\Delta\lambda_i}\right)\sum_{j=1,j\neq k}^{j=N_{elements}} V_{kj}F_{k\to j}B_{j,\Delta\lambda_i}$$

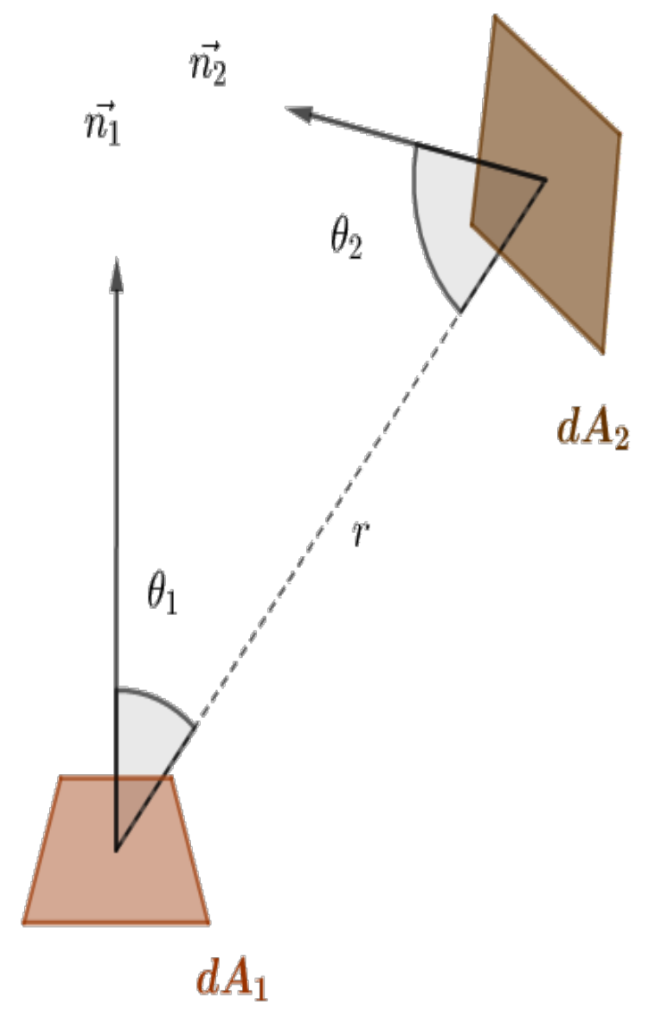


Fig. 1 : Geometry for two infinitesimals elements

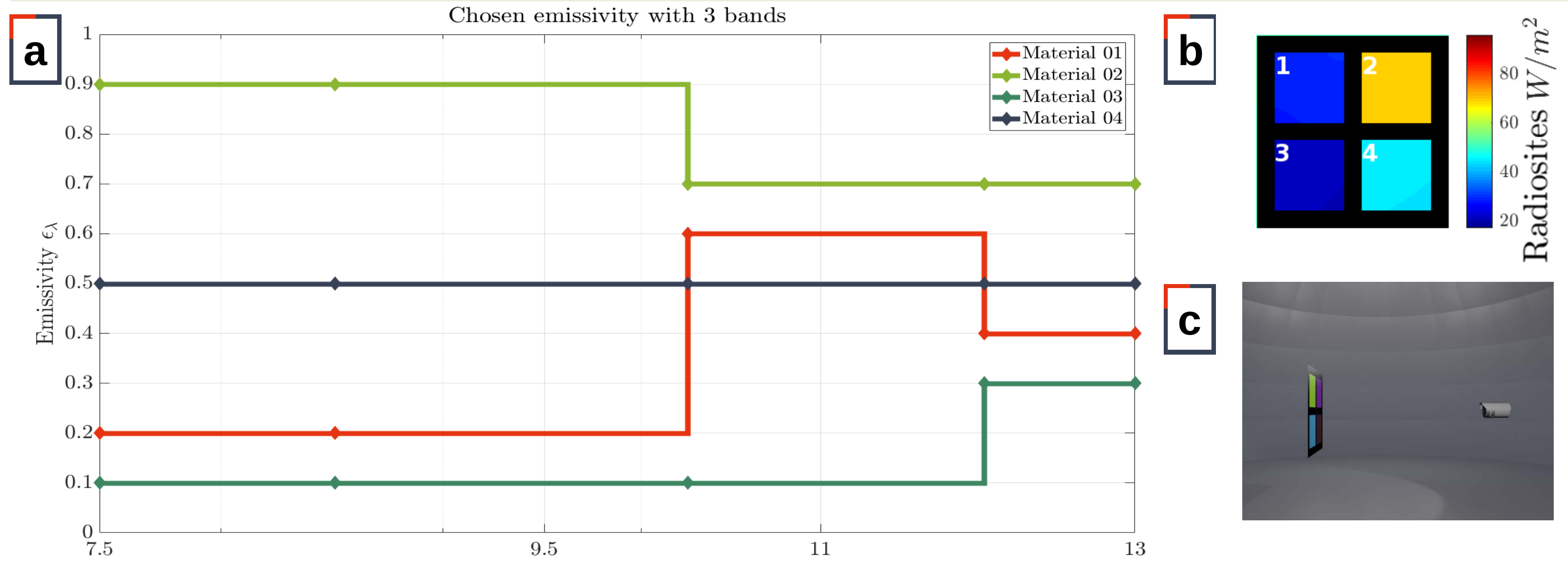
C++ Implementation

- GPU acceleration through OpenGL's API
- User-friendly graphical interface
- Python interpreter for user-case scenarios
- Use models from literature :
  - ⇒ Get the solar spectral radiation at ground
  - ⇒ Sensor model for radiative illumination to image

3D Model

A target with 4 different materials properties

a **b** **c**



d

T (K)		T (K)	
Simulation 1	293.15	Simulation 3	333.15
Simulation 2	313.15	Simulation 4	353.15

Fig. 2 : (a) Spectral emissivity distribution of 4 artificial materials for the target in the $7.5\mu m - 13\mu m$ bandwidth
(b) Simulation results for $T = 313.15K$
(c) Camera, target and environment in the visible
(d) Temperature ranges

Temperature and emissivity retrieval

With Bouguer's law and for infinitesimal surfaces[2]:

$$E_{\mathrm{sensor},\Delta\lambda_i} = \frac{I_{object,\Delta\lambda_i}\cos(\theta_{sensor})}{r^2} = \frac{\cos(\theta_{object})\cos(\theta_{sensor})\, dS_{object}}{r^2} L_{object}\,(\Delta\lambda_i, T)$$

⇒ Undetermined system with $\boldsymbol{\epsilon_{\Delta\lambda_i}}$ and $\boldsymbol{T}$ unknowns

$$E_{\mathrm{capteur},\Delta\lambda_i} = g\left(\theta_{capteur}, \theta_{objet}, r\right)\boldsymbol{\epsilon_{\Delta\lambda_i}}\mathrm{L^o}(\Delta\lambda_i, \boldsymbol{T})$$

Compared methods

Non linear optimization

$$\operatorname{argmin} \sum_{i=1}^{N}\left[\gamma_{\Delta\lambda_i} - \epsilon_{\Delta\lambda_i}\int_{\Delta\lambda_i} L^o(\lambda, T)d\lambda\right]^2$$

$$\epsilon_{\Delta\lambda_i} = \sum_{j=0}^{M} a_j\Phi_j(\Delta\lambda_i)\,;\quad 0 \leq \epsilon_{\Delta\lambda_i} \leq 1;$$

$(\Phi_j)_{1\leq j\leq M}$ orthonormal basis (Tchebychev-1)

$$200K \leq T \leq 400K$$

« Temperature Emissivity (TES) Method »[3]

$$T(\Delta\lambda_i) = L^{o^{-1}}\left[\frac{\gamma_{\Delta\lambda_i} - L_{env}(\Delta\lambda_i)}{\epsilon_{max}} + L_{env}(\Delta\lambda_i)\right],$$

$$\tilde{T} = \max_{\Delta\lambda_i}(\operatorname{sgn}\left(\gamma_{\Delta\lambda_i} - L_{env}(\Delta\lambda_i)\right)T(\Delta\lambda_i))$$

$$\tilde{\epsilon}(\Delta\lambda_i) = \frac{\gamma_{\Delta\lambda_i} - L_{env}(\Delta\lambda_i)}{L^o\left(\Delta\lambda_i, \tilde{T}\right) - L_{env}(\Delta\lambda_i)}, \beta(\Delta\lambda_i) = \frac{\tilde{\epsilon}(\Delta\lambda_i)}{\overline{\tilde{\epsilon}(\Delta\lambda_i)}},$$

$$\epsilon_{min} \approx a - b(\beta_{max} - \beta_{min})^c$$

$$\hat{\epsilon}(\Delta\lambda_i) = \beta(\Delta\lambda_i)\frac{\epsilon_{min}}{\beta_{min}}$$

Multi-temperature[4]

$$\operatorname{argmin} \sum_{i=1}^{N}\left[\gamma_{\Delta\lambda_i,T_1} - \epsilon_{\Delta\lambda_i}\int_{\Delta\lambda_i} L^o(\lambda, T_1)d\lambda\right]^2 + \left[\gamma_{\Delta\lambda_i,T_2} - \epsilon_{\Delta\lambda_i}\int_{\Delta\lambda_i} L^o(\lambda, T_2)d\lambda\right]^2$$

$$\epsilon_{\Delta\lambda_i} = \sum_{j=0}^{M} a_j\Delta\lambda_i^j\,;\quad 0 \leq \epsilon_{\Delta\lambda_i} \leq 1;\quad 200K \leq T_1 \leq 400K;\ 200K \leq T_2 \leq 400K$$

Bayesian (Monte-Carlo Markov Chain (MCMC))[5]

A priori known laws:

$$\epsilon \approx \mathcal{N}(\mu_\epsilon, \Sigma_\epsilon)$$

$$T \approx \mathcal{U}(T_{min}, T_{max})$$

With $\mu_{epsilon} = \begin{pmatrix} 0.6 \\ 0.6 \\ 0.6 \end{pmatrix}, \Sigma_{epsilon} = \begin{pmatrix} 1 & 0.8 & 0.8 \\ 0.8 & 1 & 0.8 \\ 0.8 & 0.8 & 1 \end{pmatrix}$

Draw variables ϵ and T by using the targeted distributions $p(\epsilon|\gamma)$ and $p(T|\gamma)$ with a *Slice-within-Gibbs* sampler.

Results

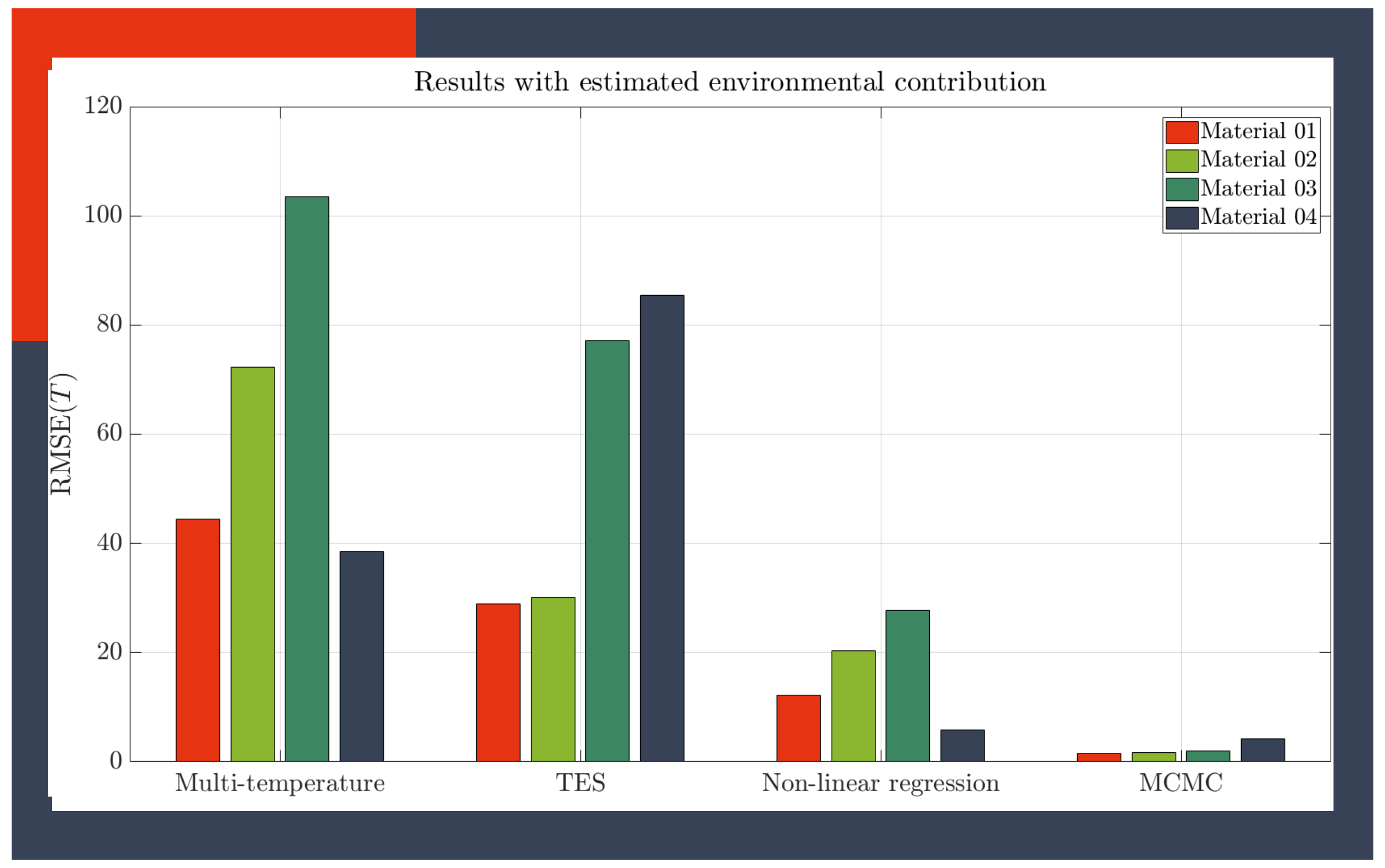


Fig. 3 : Temperature estimation for the 4 different methods

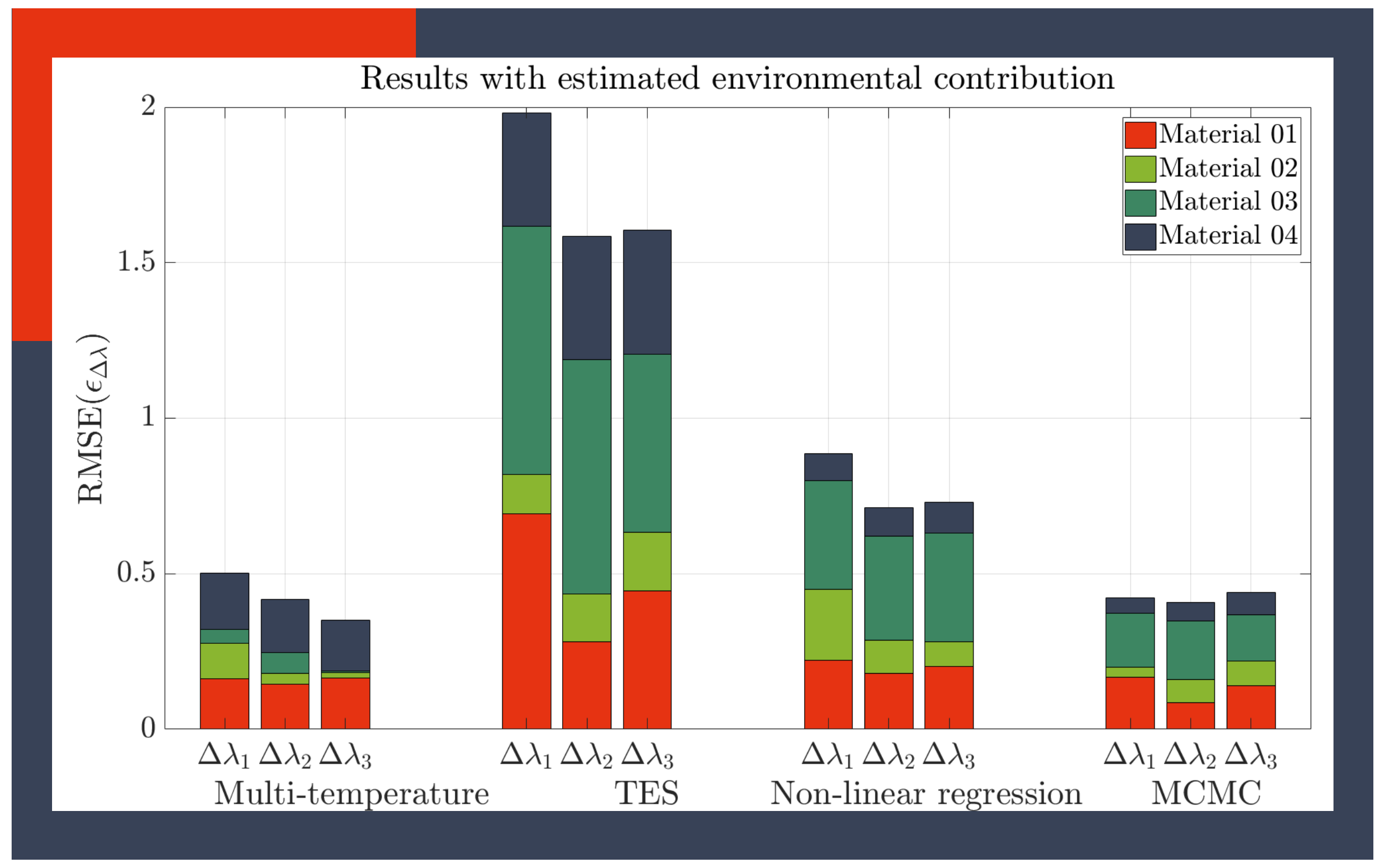


Fig. 4 : Emissivity estimation for the 4 different methods

Stopping criteria

- Optimization algorithms ⟹ local minimum
- Metaheuristic ⟹ 10000 iterations

$$RMSE(x) = \frac{1}{N_{simu}\times N_{pixels}}\sum_{k=1}^{N_{simu}}\sum_{j=1}^{N_{pixels}}\sqrt{\left(x_{k,j} - x_{objective,k}\right)^2}$$

Observations

- Non linear methods find a local minimum without any guarantee on the physical solution
- TES relies on a correlation based on a database linked with airborn based applications
- MCMC is a metaheuristic that requires a long time and effort to be computed

Conclusion and perspectives

Conclusion:

- Comparison of 4 methods to estimate simultaneously emissivity and temperature
- Study and development of a 3D scene IRT simulator

Perspectives:

- Add measurement noises in the simulation process to observe their effect
- Combine temporal and spatial information in Bayesian methods for further improvements of joint estimation

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