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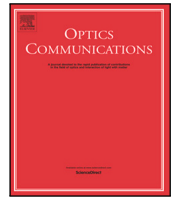
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Comment on “Multispectral radiation temperature inversion based on Transformer-LSTM-SVM”

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ABSTRACT

A recent publication (Cui et al., 2025) presents an inversion method to extract temperature from multi-wavelength radiation measurements that is claimed to be accurate despite the absence of any information on emissivity. This Comment recalls that when no information on emissivity is available, we are faced with an unsolvable problem because it has a continuous infinity of physically acceptable solutions, among which the true solution is indistinguishable from the others. It is therefore impossible to extract reliably the true temperature. No inversion or optimization method can be successful, except by chance. However, in Cui et al. (2025), the validation tests showed systematic success, which can then only be explained by the fact that the “true” solution was known in advance. When this is not the case, the inversion method cannot be better than a random draw. Blind tests of multiwavelength thermometry methods allegedly not requiring emissivity information were recently organized. The results confirmed, if proof were needed, that this approach is a dead end.

1. Introduction

This comment on [1] follows the comment [2] on [3] and the comment [4] on [5] where the same fundamental error was made, which is to ignore the fact that because passive multiwavelength radiation thermometry is an *underdetermined problem*, it has a *continuous infinity of exact solutions*.

In practice, the radiance L of the radiation emitted by the surface of interest is measured at n wavelengths λ_i , $i = 1, \dots, n$. These radiance values are related to the surface temperature T through n equations

$$L_i = \epsilon(\lambda_i, T)B(\lambda_i, T), \quad i = 1, \dots, n \quad (1)$$

where $B(\lambda_i, T)$ is the blackbody radiance at wavelength λ_i and temperature T . The emissivity $\epsilon(\lambda_i, T)$, which depends on wavelength and temperature, simply reflects the reduction in radiant flux emitted by the surface studied compared to the ideal blackbody surface at the same temperature. By principle, the emissivity is less than one and greater than zero. It depends on the material and several other factors such as direction, roughness, possible oxidation or contamination, and, as mentioned above, wavelength and temperature. It is typically an unknown parameter in addition to the temperature we are looking for. We are thus in the presence of n radiance equations and $n + 1$ unknown parameters (the n spectral emissivity values plus temperature). The

problem is thus underdetermined and has therefore a *continuous infinity of solutions*, which was overlooked in Ref. [1].

The multiplicity of solutions in multiwavelength thermometry (MWT) makes the problem unsolvable. For this reason, additional conditions or constraints on emissivity *must* be introduced, which is known from the origin of MWT, see e.g. Ref. [6–8] and the reviews in Ref. [9–11]. The constraint on emissivity can take the form of an analytical model with a number of free parameters equal to $n - 1$ at most. Alternatively, the problem can be solved in a Bayesian framework by introducing a set of a priori values and uncertainties for emissivity and/or temperature. Ref. [1] is the last of a series of papers (among which Ref. [3,5]) which defy comprehension by claiming that accurate temperature can be obtained without introducing any analytical model nor any information on emissivity. In short, the authors pretend to solve a problem known to be unsolvable. Papers on multiwavelength thermometry methods that supposedly require no emissivity information (in short MWT-NEI) have appeared in the early 2000s and their number has been rising alarmingly since 2020. A recent review of these works has shed light on their failure [12] (a periodic update of the review can be found in Ref. [13]). Obviously, there is no exception with Ref. [1]: the validation tests shown therein give the impression that temperature recovery is accurate, but this is just an illusion. Actually, in real-life situations, accuracy is clearly

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unpredictable and cannot be statistically better than a simple random guess of temperature as we will show below.

2. Biased validation tests

The inversion method proposed in Ref. [1] builds upon deep learning architecture (Transformer, Long Short-Term Memory - LSTM), and supervised learning models (Support Vector Machine - SVM). In short, six emissivity spectra were selected (Class A to Class F), with six spectral values between 1.5 and 2 μm . Fifty four other spectra were generated therefrom for diversity, though with no information on procedure or result. The emitted radiation was calculated for all these 60 spectra and 34 temperature values between 923 K and 1253 K. The network was trained on part of these data and the test results were presented for Class A to Class F and nine temperatures.

Let us consider simply Class A and Class B spectra (see Fig. 3 in Ref. [1]), and one of the studied temperatures, say 1043 K (the discussion would be the same for all other cases). The inversion method in Ref. [1] allowed to recover this temperature with only about 0.1% error when radiance data are error-free and about 1% error when radiance is affected by 5% random Gaussian error. These error values are unexpectedly low as compared to the temperature range of the solution space. The solution space is easy to evaluate as was described by Coates in Ref. [6]. The emitted radiance for Class A emissivity when temperature is 1043 K is reported in Fig. 1a. Based on this radiance spectrum, each “permitted” solution (as named by Coates) is obtained by choosing a trial value for temperature, \hat{T} , and calculating the related emissivity spectrum $\hat{\epsilon}_{\hat{T},i}$ by simply reversing Eq. (1), namely:

$$\hat{\epsilon}_{\hat{T},i} = L_i/B(\lambda_i, \hat{T}), \quad i = 1, \dots, n. \quad (2)$$

Provided that the calculated emissivity lies within a plausible range, each of these temperatures \hat{T} and related emissivity spectrum $\hat{\epsilon}_{\hat{T},i}, i = 1, \dots, n$ constitute jointly a perfectly valid solution in that it explains perfectly the measured radiance data (actually whether error-free or error-corrupted) [6]. As for the plausible range for emissivity, we can set 1 for the upper limit and typically 0.1 for the lower limit (these values may depend on the situation, but in the absence of emissivity information, we must choose a wide range). Based on this plausible emissivity range, the permitted solutions related to the radiance of Class A at 1043 K are reported in Fig. 1b. Notice that the permitted solutions constitute a continuous, henceforth infinite set. Only a small, finite subset has been represented.

The same analysis was carried out for Class B at 1043 K and the results are plotted in Fig. 2.

In both cases, the lower limit for the permitted temperature, \hat{T}_L is quite close to the “true” temperature of 1043 K; it is only about 6 or 8 K lower. This is due to the fact that the maximum value of the emissivity spectra was chosen by the authors very close to one, namely 0.95 (this can be observed for all six emissivity spectra, A to F). On the opposite, the upper limit \hat{T}_U , is 177 to 217 K higher than the “true” temperature 1043 K.

How can it be that the temperature recovered in Ref. [1] is in error by only about 1 K whereas the range of permitted temperatures is more than two orders of magnitude larger? Such a low temperature error can be explained either by chance or “information bias”, meaning the bias observed in inversion tests when the searched solution is known in advance. Chance should reasonably be discarded because similarly low errors were observed for all six emissivity classes and all 34 temperatures, meaning a highly improbable conjunction of occurrences. What remains is “information bias”. We can imagine it taking one of two forms: the application of hidden constraints or the introduction of too little diversity to the training set.

Hidden constraints consist in leveraging the knowledge we might have, for example, about the maximum and minimum values of the “true” emissivity spectrum (see, e.g. Ref. [4,5]). For example, increasing the lower limit of the plausible emissivity range from 0.1 to 0.32

decreases \hat{T}_U from 1220 K to 1053 K, thus reducing the range of permitted temperature to less than 1% on either side of 1043 K. By further reducing the plausible emissivity range, the range of permitted temperature can be easily reduced to 0.1%. However, firstly, such knowledge contradicts the claim that the method requires no information on “true” emissivity. Secondly, if such knowledge were available, there is no need to use complicated inversion methods like that in Ref. [1], it is enough to draw the permitted solutions as in Fig. 1b or Fig. 2b, and find out those between the said maximum and minimum emissivity values.

Regarding the second hypothesis (too little diversity of the training set), nothing was said in Ref. [1] about how the six spectra chosen initially were “generalized”. It was only mentioned that “A combination of 60 emissivities is designed under each emissivity model to make the experimental data more general”. If full generalization had really been achieved, any of the permitted solution shown in Figs. 1b and 2b (as well as any intermediate permitted solution) should have been rendered by the inverse method. The inverse method would then have indicated to the authors that the problem is unsolvable because of the impossibility to find the “true” solution among all these permitted solutions.

An analysis of the code used in Ref. [1], would easily provide the reason why the inversion method systematically led to a result close to the “true” solution (i.e. the target solution) and ignored all other permitted solutions. There is no denying that the inversion method incorporates a kind of supervision, i.e. a guidance process towards the target solution. The supervised inversion relies on a prior knowledge of the “true” emissivity spectrum, which is in contradiction with the claim of the authors that no information on “true” emissivity is necessary.

To conclude on these validation tests, the errors that the authors obtained in Ref. [1], whether with error-free radiation data or error-corrupted, highly underestimate the uncertainty in temperature when the true emissivity is really unknown.

3. General failure

The effort the authors put into making their supervised method converge almost perfectly on the emissivity spectra and temperatures used to build the network turns out to be useless when it comes to proving the effectiveness of their method in the general case.

The validation tests discussed before consisted in selecting any among six emissivity spectra, calculate the emitted radiation for a given temperature, apply the inverse method on the radiation spectrum and retrieve the emissivity spectrum and the temperature. Let us abandon the validation test scenario and move on to real-life processing. In real-life experiments, we have at hand a set of multiwavelength radiance data and the objective is to infer the temperature of the observed surface, and incidentally to evaluate the emissivity spectrum. Let us imagine that the radiance spectrum is that represented in Fig. 1a. Suppose that we do not know anything about the true emissivity. The true emissivity spectrum could be any of the permitted spectra represented in Fig. 1b since each of them, with the temperature reported on the right-hand side, perfectly explains the radiance data in Fig. 1a. As an example, let us assume that the true emissivity spectrum is the permitted spectrum corresponding to the temperature value 1193 K. The inverse method developed in Ref. [1], when applied to the radiance spectrum in Fig. 1a will invariably tell us that the temperature is a value close to 1043 K, to within about 0.1%, as reported in Fig. 4. Using the previous example of a true temperature of 1193 K, this amounts to an error of 150 K, i.e. over 12%. In fact, sticking to the 1043 K response (for the presently considered radiance spectrum), the inverse method makes an error of between +8 K and -177 K (i.e. between +0.7% and -14.5%), depending on whether the true spectrum is the upper or lower one in Fig. 1b. From this we can deduce that selecting a value at random between \hat{T}_L and \hat{T}_U (i.e. 1035 and 1220 K), would not give statistically worse results than applying the inverse method proposed in Ref. [1]. This can be generalized to any other emissivity spectrum or

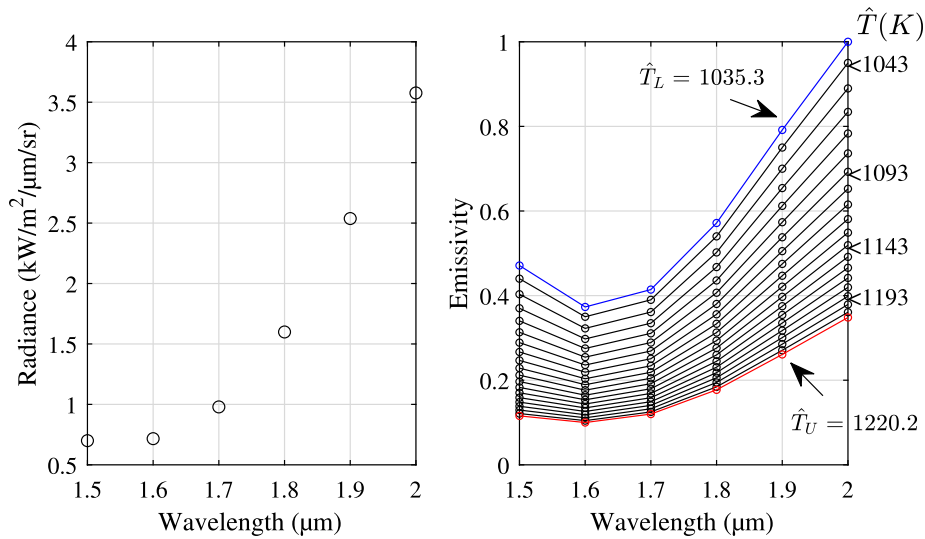


Fig. 1. a: Emitted spectral radiance for the emissivity Class A (Fig. 3 in Ref. [1]) and $T=1043$ K. b: Trial temperature values \hat{T} and related emissivity spectra $\epsilon_{\hat{T}}(\lambda)$ all leading exactly to the observed radiance shown at left. They are part of the infinite set of permitted solutions. The emissivity spectrum associated to the lower permitted temperature, \hat{T}_L , i.e. such that $\max(\epsilon_{\hat{T}}(\lambda))=1$, is in blue. That associated to the upper permitted temperature, \hat{T}_U , i.e. such that $\min(\epsilon_{\hat{T}}(\lambda)) = \epsilon_{min}$, which was here set to 0.1, is in red. The lines between the six spectral data are drawn for ease of reading only.

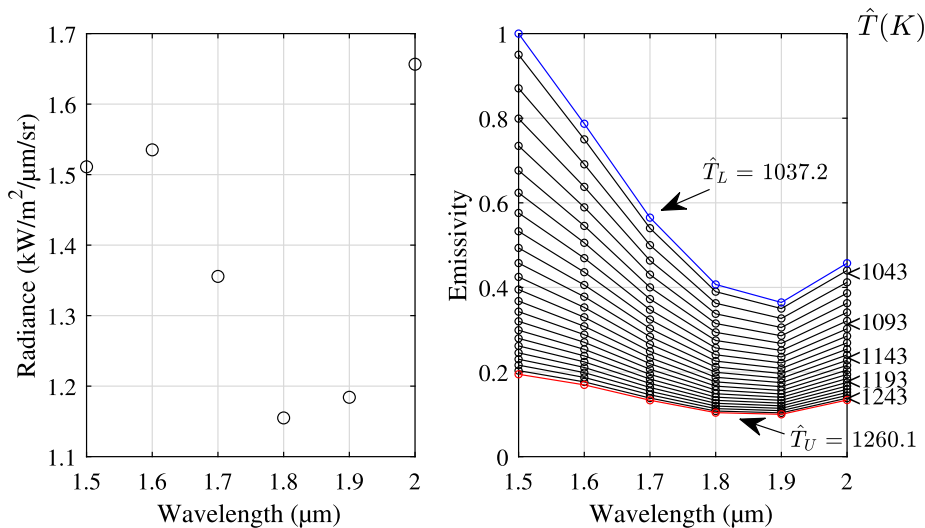


Fig. 2. Same for the emissivity Class B.

temperature, and therefore proves the general failure of the inversion method.

The same failure would inevitably occur with any inverse/optimization method when no information about the true emissivity is used. This, in the end, is of no surprise.

In fact, MWT-NEI methods were thoroughly reviewed and assessed in Ref. [12]. Blind tests were even organized to rule out any risk of “information bias”. The results proved the failure of all tested MWT-NEI methods (one of the authors of Ref. [1] participated to these blind tests). It is perfectly logical that the failures observed in the blind tests described in Ref. [12] can be generalized to any other MWT-NEI method, since all these methods suffer from the same fundamental conceptual error, namely the illusion of being able to extract the true solution from an infinite set of iso-response solutions. With complete certainty, the MWT-NEI method presented in Ref. [1] and all similar methods previously published by the same authors [14–25] can only fail blind tests. We can safely make this generalization simply because every MWT-NEI strives to produce a unique solution, while there are

infinitely many solutions among which the true solution remains hidden. It remains so as long as no information about the true emissivity is used to identify the true spectrum. The discussion about the real-life experiment at the beginning of Section 3 is another way of proof of the deadlock.

The application of the inversion method in Ref. [1] to experimental data has been claimed to provide accurate temperature measurements, i.e. with an error less than about 1%. In view of the discussion above, these unexpectedly good results necessarily stem from an “information bias” again: the true temperature was measured by another means, hence the true emissivity spectrum was known in advance. Note that the emissivity range of the nickel-based alloy GH3044 is a maximum of 0.2 in the spectral band $[1.5\mu\text{m}, 2.0\mu\text{m}]$ over a wide range of oxidation states [26]. This is well below the range of 0.6 considered by the authors for the emissivity targets Class A to Class F. Reducing the range from 0.6 to 0.2 significantly increases the range of permitted temperatures, $[\hat{T}_L, \hat{T}_U]$. As an example, when assuming that emissivity linearly decreases from 0.7 to 0.5, these temperature limits change into resp. 1004 K and 1322 K (for a true temperature at 1043 K), making it

all the more urgent to introduce information on true emissivity for an efficient temperature identification.

4. Conclusion

MWT is an underdetermined problem which, without emissivity information to add constraints, remains an unsolvable problem. No neural network, genetic algorithm, or optimization method, no matter how sophisticated, will change that. The aim of this Comment was to establish that the claim of Ref. [1] that temperature can be accurately assessed without emissivity information is illogical. The results of the validation tests in Ref. [1] are far too optimistic, the only explanation being that the target data were known in advance and used to supervise the inversion method. When the true emissivity is really unknown beforehand (e.g. in a blind test), the method unavoidably fails (if we exclude a small probability of success by chance). The same happens with any other inversion/optimization method.

Believing that temperature can be recovered without information on emissivity is like believing that we can find two unknown parameters $A \in]0,1[$ and B knowing only their product. The dimension of the solution space is one in both cases and we remain stuck with a continuous infinity of perfectly valid solutions. Pondering on either of these two problems is a waste of time and of no scientific interest.

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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