Sub-pixel target detection in LWIR hyperspectral imagery using ground leaving radiance

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ABSTRACT

The processing chain leading to specific material detection in hyperspectral imagery implies the use of atmospherically corrected images of emissivity or reflectance before comparing image signatures to a database of materials' signatures. This is a sensible approach for the reflective hyperspectral bands l and when the pixels are completely filled with a uniform material in the LWIR bands (8 to 12 microns). In the LWIR, the atmospheric correction process is different of what is used in the reflective bands and involves the use of a temperature and emissivity separation process (TES). If the pixel is not filled with a uniform material and the measured radiance is produced from the mix of materials having different emissivity and temperatures, the output of the TES will not be linear in temperature and in emissivity and will be contaminated by the non-linear mix of the temperature and emissivity of the materials leading to a potential for confusion during the detection process. In this paper, we propose a detection approach using the ground leaving radiance that is used directly to perform detection using emissivity signatures contained in a database. The detection results using this process are compared with the detection results using the output of a TES algorithm. The study is performed in simulation without noise and with the exact knowledge of the downwelling irradiance. The results show that a detection algorithm using the ground leaving radiance performs better than its counterpart using the emissivity when the difference in temperature increases.

Index Terms— Hyperspectral, detection, LWIR, Atmospheric correction, Temperature and emissivity separation

1. INTRODUCTION

In the LWIR (Long wave Infrared) extending from 8 to 12 microns, the properties of the signal are different from what can be seen in the reflective part of the spectrum for wavelengths shorter than 4 microns. Material detection in a homogenous pixel can be performed in a similar manner to what is done in the reflective bands that is by extracting the temperature and the emissivity of the material covering the pixel and then by comparing the pixel emissivity signature to a database of known materials signatures. When the pixel contains a mixture of materials, the properties of the radiance are different since the signal is a mixture of radiance and cannot be assimilated to a mixture of emissivity signatures, mainly because the temperature differences between the materials composing the pixel introduce a modulation in the emissivity signature. This is due to the self-emission contribution of the materials in the LWIR. To take that into account, we developed an algorithm which performs detection by directly using the measured radiance, the background radiance and the downwelling irradiance. The algorithm based on radiance processing is developed in section 2 then its detection performances are compared with the detection performance of a similar detection technique based on the emissivity. The proposed algorithm iterates on the temperature of the material to detect. The simulated emissivity data that were used come from the ASTER spectral library [1] and the temperature emissivity separation algorithm that is used is DEFILTE [2]. The objective of the paper is to compare the orthodox method of extracting temperature and emissivity before using a detection algorithm to the proposed method of targeted extraction of temperature and emissivity. The comparison of different TES algorithms and the introduction of noise in the simulation are devoted to later work and are not in the scope of this work.

2. ALGORITHM DEVELOPMENT

The assumptions behind the development of the algorithm are:

a. The background is uniform enough around the pixel of interest that it can be modeled using its average;

b. The variance and covariance of the background radiance is negligible;

c. The atmospheric compensation of the image has been performed and therefore we have the ground leaving radiance;

d. The downwelling irradiance for the scene is available;

e. The temperature and the emissivity of the background pixels are available;

f. The ground leaving radiance of the pixel of interest is a linear mix between the radiances of the background and of the material to detect.

The background ground leaving radiance can be expressed by:

$$R_b = \varepsilon_b B(T_b) + (1 - \varepsilon_b)L \qquad (1)$$

The contamination material ground leaving radiance can be expressed by:

$$R_s = \varepsilon_s B(T_s) + (1 - \varepsilon_s)L \qquad (2)$$

Where, $\boldsymbol{R_b}$ and $\boldsymbol{R_s}$ are the ground leaving radiance of the background and of the material; $\boldsymbol{\varepsilon_b}$ and $\boldsymbol{\varepsilon_s}$ are the emissivities, $\boldsymbol{T_b}$ and $\boldsymbol{T_s}$ are the temperatures, $\boldsymbol{B}$ is the Planck's blackbody radiation law and $\boldsymbol{L}$ is the downwelling irradiance.

The expression for the linear mix is:

$$R = (1 - a)R_b + aR_s \qquad (3)$$

Where $\boldsymbol{R}$ is the ground leaving radiance and $\boldsymbol{a}$ is the proportion in surface of the contamination material. The ground leaving radiance can be expressed as:

$$R = \varepsilon_b B(T_b) + (1 - \varepsilon_b)L + a(\varepsilon_s B(T_s) - \varepsilon_b B(T_b) + (\varepsilon_b - \varepsilon_s)L) \qquad (4)$$

The unknowns are the material temperature $\boldsymbol{T_s}$ and the proportion of its contribution in the pixel $\boldsymbol{a}$. A least square approach can be used to determine the unknowns, which leads to:

$$E^2 = [(R - \varepsilon_b B(T_b) + (1 - \varepsilon_b)L) - a(\varepsilon_s B(T_s) - \varepsilon_b B(T_b) + (\varepsilon_b - \varepsilon_s)L)]^2 \qquad (5)$$

Minimizing with respect to $\boldsymbol{a}$ yield for $\boldsymbol{a}$ and $\boldsymbol{E^2}$:

$$a = \frac{\begin{pmatrix} R - \varepsilon_b B(T_b) + \\ (1 - \varepsilon_b)L \end{pmatrix}\begin{pmatrix} \varepsilon_s B(T_s) - \varepsilon_b B(T_b) + \\ (\varepsilon_b - \varepsilon_s)L \end{pmatrix}}{(\varepsilon_s B(T_s) - \varepsilon_b B(T_b) + (\varepsilon_b - \varepsilon_s)L)^2} \qquad (6)$$

And the discriminator becomes:

$$E^2 = \begin{pmatrix} R - \varepsilon_b B(T_b) + \\ (1 - \varepsilon_b)L \end{pmatrix}^2 + \frac{\left[\begin{pmatrix} R - \varepsilon_b B(T_b) + \\ (1 - \varepsilon_b)L \end{pmatrix}\begin{pmatrix} \varepsilon_s B(T_s) - \varepsilon_b B(T_b) + \\ (\varepsilon_b - \varepsilon_s)L \end{pmatrix}\right]^2}{(\varepsilon_s B(T_s) - \varepsilon_b B(T_b) + (\varepsilon_b - \varepsilon_s)L)^2} \qquad (7)$$

In the emissivity domain, the least square formalism leads to the following expressions for the proportion of material and for the discriminator.

$$a = \frac{(\varepsilon - \varepsilon_b)(\varepsilon_s - \varepsilon_b)}{(\varepsilon_s - \varepsilon_b)^2} \qquad (8)$$

$$E^2 = (\varepsilon - \varepsilon_b)^2 - \frac{\left((\varepsilon - \varepsilon_b)(\varepsilon_s - \varepsilon_b)\right)^2}{(\varepsilon_s - \varepsilon_b)^2} \qquad (9)$$

For both approaches the material to detect is the one providing the minimum value of the discriminator. The discriminator corresponding to equation (7) is estimated iteratively with the temperature. In the case of equation (8) there is no iteration, however the TES algorithm estimates iteratively the temperature of the pixel. The output emissivity of the TES algorithm has the following form:

$$\varepsilon = \varepsilon_c + \frac{(1 - a)\Delta(B(T_b) - L)}{aB(T_c) + (1 - a)B(T_b) - L} \qquad (10)$$

Where $\Delta = \boldsymbol{\varepsilon_c} - \boldsymbol{\varepsilon_b}$ and $\boldsymbol{\varepsilon_c}$ and $\boldsymbol{T_c}$ are respectively the emissivity and the temperature of the material. The second term of equation (10) vanishes when the temperatures of the material and the background are the same or if the difference between the emissivities of the background and of the material is small. The potential for confusion between emissivity signatures in a database is due to this last term and no temperature and emissivity separation algorithm will make it disappear.

3. RESULTS COMPARISON

We performed simulations to compare the results of the two methods using 89 emissivity signatures obtained from the ASTER spectral library. The simulations consisted in varying with the temperature contrast between the background and the material and varying the proportion of the surface occupied by each in the pixel. No noise was added. Figure 1 shows a plot of the radiance obtained for a proportion of material of 0.25 for a 5K temperature contrast between the background and the material. Figure 2 shows a MODTRAN output of a high resolution plot of the downwelling irradiance. Figure 3 is a plot of the background emissivity from the file grass .txt of the ASTER spectral library and the material in black is the file sandst7c.txt. The database is shown bulk in figure 4. This figure gives an idea of the diversity and variations of the emissivity signatures.

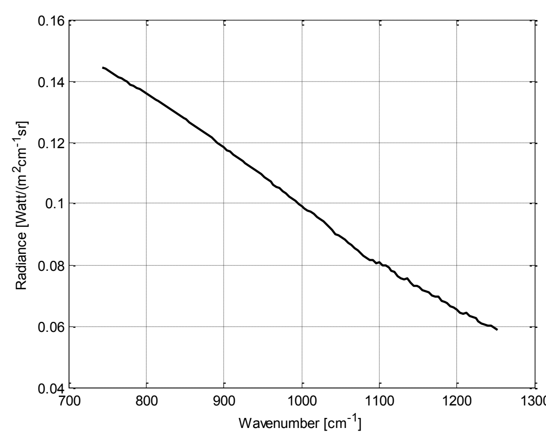

Figure 1: Ground leaving radiance example involving a proportion of 0.25 of the material with T=300K and a proportion of 0.75 of the background with T=305K.

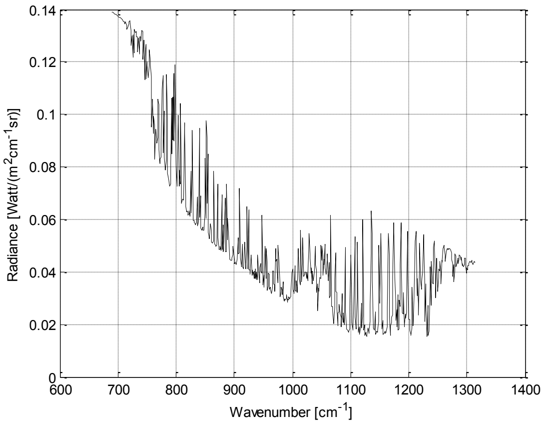

Figure 2: Downwelling irradiance example for mid latitude summer standard atmospheric profile of MODTRAN

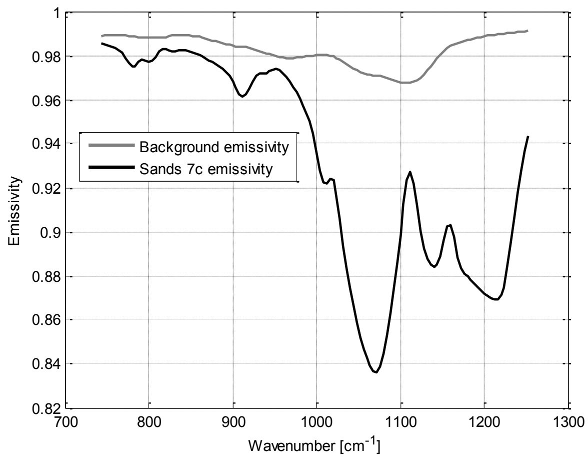

Figure 3: In grey, a plot of the emissivity of grass (background) and in black, the emissivity of sand (material to detect) used in figure 1. The data correspond respectively to the files grass.txt and sandst7c.txt of the ASTER spectral library

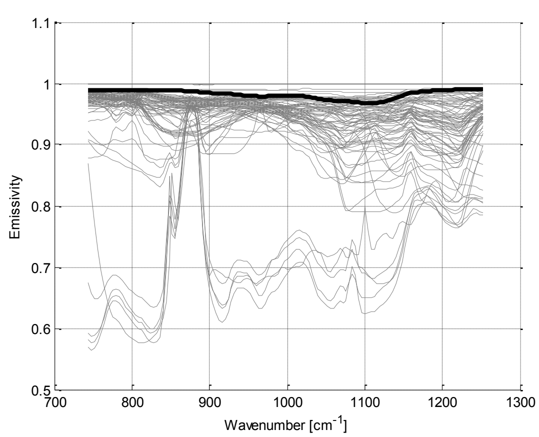

Figure 4: Plots of all of the entries in the database from the ASTER spectral library. The grass background is plotted in black.

Figure 5 is a plot of the classification results obtained from the least square algorithm in the radiance domain where the proportion of material is estimated directly and where the algorithm iterates on the temperature to find the minimal error. Figure 6 is a plot of the least square results obtained from same data, but for which we used the DEFILTE algorithm to obtain the emissivity and the temperature of the mix of the two materials with the same 5 degree contrast and a 0.25 proportion for the material.

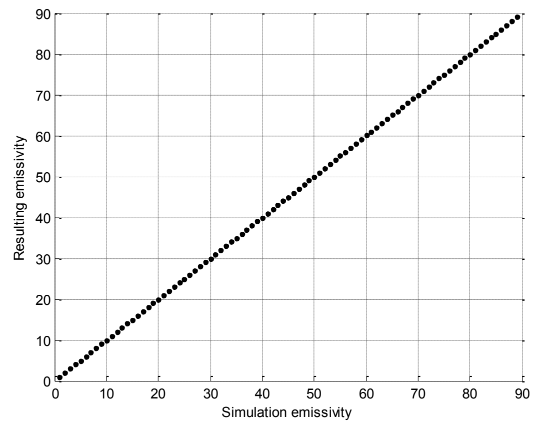

Figure 5: Classification results for the LS algorithm operated in the radiance domain for a contrast of 5 degrees in temperature and a proportion of 0.25 in surface occupied by the material.

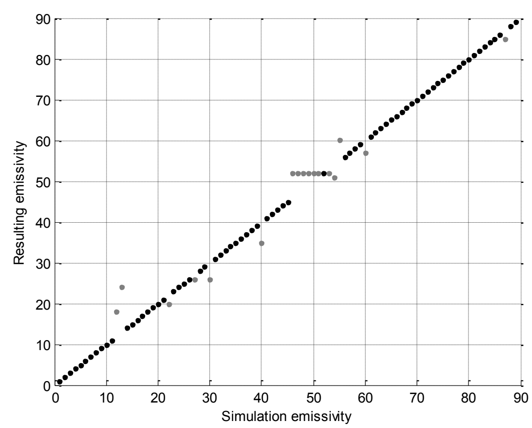

Figure 6: Classification results for the LS algorithm operated in the emissivity domain for a contrast of 5 degrees in temperature and a proportion of 0.25 in surface occupied by the material.

Tables 1 and 2 show out of the 89 emissivities the quantity of error or confusion between emissivities when using the two detection algorithms. An error occurs when the identified material if different of the simulation material. The table 1 gives the number of errors made when using the radiative approach proposed in this paper and table 2 gives the number of errors made in the detection when equation (9) and the TES algorithm are used.

Temperature Proportion%	-10	-8	-6	-4	-2	0	2	4	6	8	10
5	0	0	0	0	3	5	0	0	0	0	0
15	0	4	2	1	0	0	0	0	1	0	0
25	0	0	4	5	6	6	1	1	1	0	0
35	0	0	2	7	7	7	2	5	0	0	0
45	0	1	0	6	7	7	5	3	0	0	0
55	0	5	0	5	10	7	6	1	0	0	0
65	0	4	0	3	7	6	5	0	0	0	0
75	0	6	0	2	7	6	4	0	0	0	0
85	0	1	0	0	7	6	2	0	0	0	0
95	0	0	0	0	5	5	0	0	0	0	0

Table 1: Number of confusion errors in detection of the 89 material emissivity signatures when the temperature and the proportion of material are varied using the radiance approach (Eq. 7). The columns represent temperature differences with the background and the rows are the proportion of the material relative to the background

Temperature Proportion%	-10	-8	-6	-4	-2	0	2	4	6	8	10
5	80	62	38	15	8	5	8	11	19	28	43
15	59	63	40	12	7	0	9	14	20	29	38
25	53	44	36	14	7	0	9	14	23	24	28
35	52	31	27	14	7	0	8	11	15	18	23
45	48	27	18	13	7	0	8	10	11	11	15
55	42	22	16	12	7	0	9	10	11	9	11
65	31	16	15	10	7	1	9	10	10	10	9
75	25	13	11	9	8	4	11	13	13	13	12
85	14	14	12	10	6	4	10	11	13	14	14
95	15	12	11	11	4	4	4	10	11	11	12

Table 2: Number of confusion errors in detection for the 89 material emissivity signatures when the temperature and the proportion of material are varied using the emissivity approach (Eq. 9). The columns represent temperature differences with the background and the rows are the proportion of the material relative to the background

4. CONCLUSION

The least square algorithm is compared in the radiance domain and in the emissivity domain without noise. In the radiance domain, the algorithm operates iteratively to search the minimum of the error function as a function of the proportion of material and of the temperature. The confusion is evaluated using 89 emissivity functions obtained from the ASTER spectral library.

There is less confusion in the detection results when using the radiance approach compared to the emissivity approach when the temperature difference between the material and the background is high. The advantage of operating in the radiance domain decreases when the temperature difference between the background and the material decreases. This may be due to the iterative process of the material temperature selection that is used in the radiance approach. The radiance approach decreases the confusion between the different entries of the database when the temperature differences are higher than 4 degrees making it a more accurate approach.

The conditions in which the results are obtained are close to be optimal since there is no noise and the downwelling irradiance is known. There are other TES algorithms than DEFILTE that can be used to extract the temperature and the emissivity from the radiance, but because there is no noise and the downwelling irradiance is known using any other TES algorithms would yield comparable results.

In a future study, the impact of noise and incorrectly atmospherically compensated data shall be studied. The most important conclusion of this study is that operating subpixel detectors in the radiance domain should provide better detection performance, especially if the signature of the searched material is well known. Additional work is required to find mathematical operators better suited than the least square method to process the data. Methods based on the Generalized Likelihood Ratio Test (GLRT) are good candidates [3,4,5]. Linear filters such as whitening operators or background suppression can be added to the technique to consider background variability.

5. REFERENCES

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