On the Flame Spectrum Recovery by Using a Low-Spectral Resolution Sensor

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Abstract. In this paper, the Maloney-Wandell and Imai-Berns recovering spectrum techniques are evaluated to extract the continuous flame spectrum, by using three principal components from training matrices constructed from a flame's spectrum database. Six different sizes of training matrices were considered in the evaluation. To simulate the Maloney-Wandell and Imai-Bern methods, a commercial camera sensitivity was used as a base in the extraction process. The GFC (Goodness-of-fit coefficient) and RMSE (Root-mean-square error) quality metrics were used to compare the performance in the recovering process. The simulation results shown a better performance by using the Maloney-Wandell method in the recovering process, with small sizes of training matrices. The achieved results make of the recovering-spectral techniques a very attractive tools for designing advanced monitoring strategies for combustion processes.

Keywords: recovering techniques, flame spectrum, optical sensors.

1 Introduction

It is known that the flame spectrum conveys important information about the combustion state. Thus, optical sensing of flame spectral emission by using non-intrusive methods is nowadays an important field of development which has been tackled by using several active/passive optical sensors (like lasers, CCD cameras, photodiodes, photomultipliers, radiometers, among another) [1, 2].

However, the sensors/techniques mentioned above are limited in the extraction of spatial-spectral information from flames simultaneously. For example, the use of CCD cameras in combustion process monitoring, is based mainly in the correlation between spatial flame's morphology with combustion parameters like the air excess [3]. However, the spectral information of such flame it can not be extracted, until now, with this device, due to the low spectral-resolution (normally, three channels R, G and B).

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It is known that if we want to measure the spatial distribution along the flame of such spectral information, it should be strictly necessary to use an hyperspectral camera system, because both the spatial and spectral information are extracted simultaneously [4,5]. However, the main disadvantage of these systems is the low-time of image acquisition, making impossible to use this system in sensing the spectral information in real-time from the flame.

In this paper a first approach in the continuous flame's spectrum extraction by using the sensitivity of a trichromatic RGB camera is evaluated by using the Maloney-Wandell and Imai-Berns estimation methods [6, 7], owing to the accurate results they provide. That is, the idea is to extract a high spectral resolution spectrum by using the data given by a low-spectral resolution sensor, like a camera. These methods are based on a priori knowledge of the kind of spectra we want to recover, which can be performed by using principal components analysis (PCA), nonnegative matrix factorization (NMF) or independent component analysis (ICA). This is accomplished through the construction of a training matrix containing previously database spectral measurements, which can be linearly combined to reconstruct an unknown spectrum from the sensor's array signals. That is, any spectrum can be expressed by:

$$E_{N \times 1} = V_{N \times n} \cdot \epsilon_{n \times 1} \quad (1)$$

where V is a matrix containing the n *representative* spectrums extracted from the training matrix at N wavelengths and the vector ϵ contains the coefficient of the linear combination. The n *representative* spectrums should maintain much of the original *information* of the original spectrum. The recovering-spectrum process start assuming that the optical sensor's array have a linear response. Thus, and in absent of noise, the optical sensor's response can be modeled as:

$$ck_{k \times 1} = \omega_{k \times N}^t \cdot E_{N \times 1} \quad (2)$$

where ck is the optical sensor response of the k channel (in a RGB camera, for example, the array is composed by $k = 1, 2$ and 3), ω^t is the transposed of the matrix containing the spectral sensitivity (responsivity and filters transmissions) of the sensors, and E is the spectrum impinging in the optical array. In the following, a brief description of the below algorithms is given.

2 Brief Descriptions of Recovering-Spectrum Algorithms to be Evaluated

In this section, a brief description of the Maloney-Wandell and Imai-Berns estimation methods is given.

2.1 Maloney-Wandell Recovering-Method

The recovering process of E (that is $\hat{E}$, at N wavelength samples) is achieved by found a matrix which transform the sensor's array responses ck in the coefficient

of the linear combination, ϵ . This is performed by replacing the Eq. (1) into Eq. (2):

$$ck_{k \times 1} = \omega_{k \times N}^t \cdot V_{N \times n} \cdot \epsilon_{n \times 1} \quad (3)$$

$$ck_{k \times 1} = \Lambda_{k \times n} \cdot \epsilon_{n \times 1} \quad (4)$$

that is, the pseudoinverse of Λ (Λ^+) directly transform the sensor's array response in the coefficient needed for the linear estimate of the spectrum from the sensor's response. Therefore, and replacing on Eq. (1), the estimated (recovered) spectrum can be calculated as:

$$\hat{E}_{N \times 1} = V_{N \times n} \cdot \Lambda_{n \times k}^+ \cdot ck_{k \times 1} \quad (5)$$

Note that the spectral-dimensionality (wavelength resolution) of the recovered spectrum depends on the spectral-dimensionality of the training matrix. On the other hand, the recovered spectrum directly depends on the spectral sensitivity of the optical system (inserted on Λ^+), and therefore the optimum spectral characteristics of the optical system (i.e responsivity and filters transmission) should be estimated at different applications.

2.2 Imai-Berns Recovering-Method

The main difference between this method versus the above described (Maloney-Wandell) is which in this case it is not necessary to know the spectral responsivity of the sensors, but sacrificing accuracy in the recovered process. This method is based directly on found empirically a relationship between the sensor's response c_k for each spectrum m contained in the training matrix and the coefficients ϵ from the principal components. That is, for each m spectrum it is measured the sensor's responses, which can be combined with the respective coefficients like:

$$\epsilon_{n \times m} = G_{n \times k} \cdot ck_{k \times m} \quad (6)$$

In this case, the information provided by the training matrix is included on G . Therefore, by pseudoinverting the sensor's response matrix ($ck_{k \times m}^+$) we can found the matrix G which allow us to estimate (to recover) the spectrum from:

$$\hat{E}_{N \times 1} = V_{N \times n} \cdot G_{n \times k} \cdot ck_{k \times 1} \quad (7)$$

3 Metrics for Quality Evaluation in the Recovering Spectrum Process

Different metrics to quantify the quality in the reconstruction process have been traditionally used [8,9], like the root-mean-square error (RMSE) and the goodness-of-fit coefficient (GFC). The GFC metric is based on the Schwartz's inequality [10], and is defined as:

$$GFC = \frac{\left| \sum_j E(\lambda_j) \hat{E}(\lambda_j) \right|}{\left[\left| \sum_j [E(\lambda_j)]^2 \right| \left| \sum_j [\hat{E}(\lambda_j)]^2 \right| \right]^{1/2}} \quad (8)$$

where E is the original measured sample data at the wavelength λ_j and $\hat{E}$ is the recover spectrum at the wavelength λ_j . Accurate estimation require $\text{GFC} > 0.995$. $\text{GFC} > 0.999$ mean quite good spectral matches, and $\text{GFC} > 0.9999$ an excellent spectral match.

4 Recovering Continuous Flame Spectrum Using Simulated Camera Responses

Both, Maloney-Wandell and Imai-Berns recovering-methods have been implemented to simulate a first approach in recover continuous flame spectrum, based on a flame spectrum's data base taken in our laboratories since 2005 with a previously calibrated USB2000 radiometer (with spectral resolution of 2048 from 339.38-1025.09 nm). Eight different training-matrices TM (with sizes of 4, 5, 6, 7, 8, 9, 20 and 40) have been constructed from where extract the respective matrix V (Eq. (1)). In order to evaluate the differences on the recovered results, the above described metrics GFC and RMSE have been calculated.

Like is mentioned in [11], three PCA basis vectors are enough to recover skylight spectra with acceptable accuracy. Assuming that the continuous flame spectrum have similar spectral-characteristics like skylight, three PCA has been extracted from the training matrices. Therefore, three spectral sensitivities bases have been selected, simulating the spectral response of a Basler A602-fc RGB camera provided by the manufacturer (Fig. 1(a)) in order to construct the matrix Λ^+ (Eq. (4)). Five calibrated spectrums (test spectrums) measured at different flame temperatures were used to be recovered (Fig. 1(b)) in the range 380-700nm.

4.1 Computational Results

In Fig. 2 it is depicted fourth different TM's which have been used in the simulation. From this TM's are extracted the respective three PCA's used to construct

Fig. 1. (a) Spectral sensitivity of the Basler A602-fc camera, (b) Flame's spectrums samples at different temperatures measured with the USB2000 radiometer

Fig. 2. Constructed training matrices TM and the respective three principal components PC , considering (a) 4 samples, (b) 6 samples, (c) 8 samples and (d) 9 samples

Fig. 3. Examples of recovered spectrum and the respective MSE by using Maloney-Wandell method with (a) with 4 samples and (b) 9 samples in the TM and by using the Imai-Bern method with (c) 4 samples and (d) 9 samples in the TM

Fig. 4. Evolution of the mean values of GFC and RMSE quality metrics calculated from 5 test samples, for different size of m (training matrix)

the respective matrix V . It can be observed with the 2 first PCA (PCA1 and PCA2) exhibit a similar behavior when the size of the training matrix increase. Therefore, it can be concluded that the third PCA (PCA3) not provide significantly information from the constructed TM's.

In Fig. 3 it is depicted the recovered spectrums and the calculated Mean-Square Error (MSE) by using the Maloney-Wandell method (Fig. 4(a) and (b)) and the Imai-Bern method (Fig. 4(c) and (d)), by using a TM of 6 and 9. It can be seen that the performance of Maloney-Wandell method in the recovering process of the continuous flame spectrum is better than the Imai-Bern method.

The evolution of the quality metrics GFC and RMSE, calculated as the mean of the metrics calculated from the test spectrums (five spectrums) it is depicted in Fig. 4 versus an increment in the size of the TM. It can be corroborated that the Maloney-Wandell method exhibit an accurate results than the Imai-Bern method, but however it can be seen that the GFC metric is not significantly enhanced with an increment in the size of the training matrix. This result can be explained because the third PCA3 tends to stabilization with an increment of the TM (Fig. 2(c) and (d)).

5 Conclusion

We have shown the performance of the Maloney-Wandell and Imai-Bern methods in the process of recover continuous flames spectrums by simulating the use of a low-spectral resolution camera and a data base of flame's spectrums. Three

principal components were extracted from different computed training matrices, where it has been observed with the 2 first PCA (PCA1 and PCA2) exhibit a similar behavior when the size of the training matrix increase. The third PCA3 not provide significantly information from the constructed TM's but however tends to stabilization with an increment of the TM.

The Maloney-Wandell method has shown a better spectral recovering process than the Imai-Bern method, by evaluating both, GFC and RMSE quality metrics, but however the performance in the recovering process not depend significantly on the size of the training matrix.

The performance achieved by using the Maloney-Wandell simulating the use of a low-spectral resolution sensor and with an appropriated training matrix of flame's spectrums makes of these techniques a very attractive tools for designing advanced monitoring strategies for combustion processes.

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