Tomography of flames in combustion chambers

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17. Juni 1996

1 Abstract

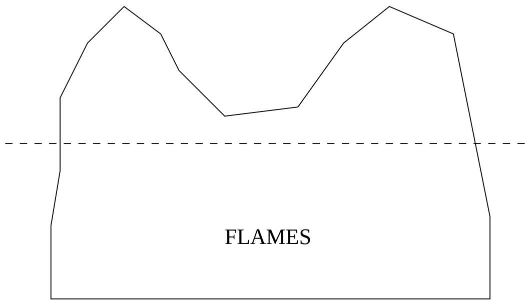
The algorithm described in this paper is to be used in large-scale combustion chambers where coal or waste are burnt. The goal is to determine the distribution of temperature and chemical radicals in the flames in order to use these for an optimal control of the burners to reduce toxic gas emission.

To this end, special cameras developped by BFI Entsorgung, Ratingen, are placed outside the chambers each of which measures the intensity of light at 1024 equally-spaced frequencies along 128 lines in a fixed plane through the flames simultaneously (see diagrams I,II). Diagram III shows a typical output delivered by one camera in one scan of the region. The x-axis has the measured frequencies, the y-axis has the angles from 0 to 90 degrees, the z-axis has the intensity of light that is actually measured.

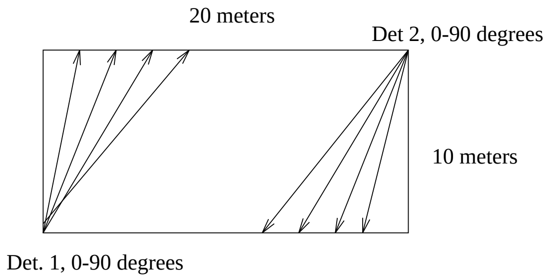
Two tomographic algorithms are then used to convert the integral data along the lines into pictures of the distribution of temperature and toxic gas.

The first one, EM (section 2), models the distribution with pixel functions. The second one, a modified ART algorithm (section 3), models the distribution with polynomial or geometric ansatz functions.

The resulting data is then fed into a classificator to derive some kind of automatic control for the chamber.



Picture I: Location of cross-section



Picture II: Cross-section

2 The EM-algorithm

Suppose the data is measured along the lines $L_1, \dots, L_m$ and the reconstruction region is subdivided into pixels $P_1, \dots, P_n$. Then a system-matrix with entries a_{ij} is computed according to $a_{ij} = \text{length}(L_i \cap P_j)$, $i = 1, \dots, m$, $j = 1, \dots, n$. It is possible to incorporate the effect of absorption by multiplying the matrix entries with an appropriate weighting factor. Let g_i be the value measured along line L_i and let f_j be the emission value in pixel P_j. If we define $A = (a_{ij})$, $f = (f_j)$ and $g = (g_i)$, we are left with the problem of solving the linear system $Af = g$. In general this system can not be expected to have a (unique) solution, so we have to compute a generalized solution. We first tried to compute the Moore-Penrose solution by using singular value decomposition or QR-factorisation, but this way wasn't very successful.

Better results are obtained by using the EM-Algorithm, which is well known in emission computerized tomography. EM is an iterative algorithm. The updating of the successive iterates is defined by $f^{k+1} = f^k * A^t \frac{g}{Af}$. Here k is the iteration index, $*$ is a component wise multiplication and the division is also component wise. If the matrix is normalized so that the sum over every column equals one, it can be shown that the vectors f^k converge to a vector f^* which maximizes the probability to measure g under the condition $f_j > 0$, $j = 1, \dots, n$.

3 ART-algorithms

An alternative to PET are classical ART-algorithms. We also tried these and found them to work very well when smooth functions (geometric functions, polynoms) are used as ansatz functions rather than the usual pixel-functions.

4 Optimal scanning geometries

The main advantage of modelling the tomographic process as described before is that it is possible to use arbitrary scanning geometries. However, it is possible to compute a solution for every scanning geometry, but it is not guarenteed that the solution makes sense. For example, it can *not* be expected that a subdivision into smaller pixels always leads to a better quality of the image. So one has to find out optimal positions for the sensors, optimal numbers of lines per fan and an optimal discretization of the reconstruction region.

Our idea was to look at the singular value decomposition of the system-matrix, and prefer those situations in which even the smallest singular values are not neglectable. The results from this idea were then confirmed by simulation studies. We have considered the cases of two, three and four fans. The reconstruction region was a circle, and the sensors were placed on the boundary of that circle.

In the two fan case we found out that it is optimal to place the sensors with an angular distance of 180 degrees. We used 91 lines per fan and have divided the smallest surrounding square in 8×8 pixels. There was no significant improvement if more than 91 lines per fan were used.

If we used three fans, it was best to position the sensors within a distance of 120 degrees, use 91 lines per fan and subdivide the square into 10×10 pixels. In the case of four fans, it was also optimal to place the sensors equally spaced in angle around the circle. Here we used again 91 lines per fan and subdivided the square into 12×12 pixels. In all cases it was also possible to use only 37 lines per fan, but then the algorithm was not stable against disturbed data.

5 Control and classification

To derive a control, the reconstructed images should be classified by a classificator. It is also possible to classify a characteristic vector, computed from the image. Such a characteristic vector can be computed by using orthogonal transforms, like Fourier- or cosine-transformation, or by statistical methods.

One classification method is the so called prototype classificator. Here every class is represented by a focal point. If a new vector has to be classified, it is first searched for the focal point with minimal distance to this vector. If this distance is less than a certain limit, than the vector is added to the class represented by the found focal point and the focal point is updated according to the new class member.

To derive a control, an initial phase is needed, in which the classes generated by the classificator are collected. An expert then has to decide, which class describes an optimal situation of the system. He also has to derive rules for every class, to direct the system to this optimal situation.

A problem of the prototype calssificator is, that it can generate a new class, every time a new characteristic vector is encountered. Our idea is just to neglect classes, wich are not generated in the initial phase.

We have also used a neuronal net as classificator, but the results were not as good as with the prototype classificator.

6 Results

Up to now, only results from laboratory-size data is available. The algorithms were found to work as expected. However, statements about accuracy and resolution in time and space can only be made when industrial-size data on real combustion chambers will be available, that is by the end of 1993.