A robust method for the quantitative shadow imaging of dense reacting particulate flows

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Quantitative shadow imaging or particle shadow velocimetry is a relatively recent method for the quantification and analysis of heterogeneous flows. Shadow imaging can yield information about the geometric characteristics of sprays, jets and particulate flows. When applied to the analysis of solid-gas or solid-liquid flows, shadow velocimetry allows for the extraction of individual particle velocities, sizes and shape parameters. An advantage of shadow imaging over other diagnostic techniques is that it retains the spatial information of individual particles and the positions of particles relative to each other can be analyzed. Another advantage is that shadowgraphy is a direct technique that allows for the visualization of microscales in heterogeneous flows. Digital image processing and analysis makes shadow imaging quantitative. By image processing techniques, individual particles are detected in the shadow images which are further analyzed to obtain their geometric and hydrodynamic properties. The fidelity of data extracted by quantitative shadow imaging depends on the quality of images and the robustness and capabilities of the image processing algorithm used. In this study we focus on the processing of very degraded shadow images of dense reacting particulate flows. An algorithm that is robust enough to reliably quantify such images does not exist yet. Such an algorithm can find its field of application in diagnosing larger scale coal flames, among others.

1 Introduction

The in situ diagnostics of particles or droplets in heterogeneous flows may yield insight on the instantaneous velocities, sizes and shapes of the observed particles. In situ methods are usually optical techniques, since the minimization of the impact of the observation is required in order to representatively study the flows. There are many optical methods for the diagnosis of heterogeneous flows and many comprehensive reviews are available on them in the literature [1–3].

Diagnostics methods for in situ particle sizing are usually laser-based methods, which apply scattering theory in order to extract particle size information [4] or combinations of laser-based methods to obtain multiple parameters of interest simultaneously [5]. Laser-based techniques usually analyze a very small volume in the flow and obtain statistical descriptors of the size information instead of individual particle sizes. Furthermore, by applying scattering theory, usually there is a need for a priori information regarding particle shapes. An exception from this is the shadow-Doppler method [6], which is a hybrid imaging-scattering approach that can diagnose particles of arbitrary shape, but still suffers from the very low analyzed volumes.
For the analysis of coal flames, a number of specialized methods were developed [7–12]. Some of these methods are capable of measuring particle size, shape, velocity and temperature simultaneously, but they are all restricted to analyzing only small volumes in flames, so that usually only a single particle is analyzed at a given instant. These methods are generally based on combinations of laser-based and pyrometric principles, thus they are not well-suited for studying the relative positions of particles and they are mostly restricted to laboratory scale flames. Information regarding the relative positions and number density maps of particles plays an important role in the study of turbulent pulverized coal flames, especially when used to validate particle models implemented in numerical simulation software [13].

There are also some studies available that discuss the optical diagnostics of coal flames by using imaging methods [14, 15]. One of these studies presented results obtained by laser-holography of a laboratory scale burner [14] and the other used shadow imaging to observe particles and combusting gas bubbles in a larger scale flame [15]. While these results demonstrate the potential of optical imaging as a diagnostic tool, they do not provide quantitative particle data. To the best of our knowledge, there has not been a study on quantitative shadowgraphy applied to a pilot-scale or larger pulverized coal flame yet.

One of the reasons of the lack of quantitative optical imaging studies on larger scale coal flames can be the difficulties in processing and analyzing the obtained shadowgraphs. Since digital shadowgraphy is a relatively new tool for characterizing heterogeneous flows, most studies utilizing it use in-house developed processing algorithms [16–18] although commercial software are available [19]. The simplest strategy for detecting individual particles in shadow images is to exploit the difference between the grayscale intensity level of the image background (which is usually bright) and the particle shadows (which are usually dark). The higher the contrast between these features, the easier to apply simple binary thresholding to the image and locate particles as connected components [20]. This simple strategy fails in two cases: if the flow is very dense and particles overlap or if the contrast between the particle shadows and background is low. For the former case, many solutions are known [21–23]. Some researchers proposed methods for dealing with the latter case: these studies use more advanced image processing [22, 24]. In these methods, the threshold intensity level for binarization is not a single pre-determined number or the thresholded image is filtered before binarization. As in the case of [24], the method is still assuming a uniform background or a known intensity distribution, by which the images can be normalized.

Dealing with de-focused particles can be done by a filtering method (as in [17]), where a gradient criterion eliminates particles that are not focused enough, or by utilizing image models [24] or calibration [18] to correct the obtained diameters of out-of-focus particles.

In the case of larger scale turbulent pulverized coal shadowgraphs, images are usually corrupted by noise and very low contrast. Furthermore, since the density gradients in these flames are typically high due to the very high temperature gradients, shadows of gas pockets and eddies can be seen in the images, along with large trails of soot. All these effects result in a "dynamic background", therefore image normalization is impossible based on an a priori known reference luminosity distribution. Low contrast is the result of insufficient backlighting power, which is usually the case when analyzing large scale flames, due to practical reasons dominating in choosing the type of light source used for imaging. In this study an image processing and analysis framework is presented, with which the robust analysis and quantification of such degraded shadow images is possible.
The framework presented here is a generic pattern recognition system, applicable to many different tasks - in this paper the capabilities of the method and preliminary results are demonstrated using shadow images of a laboratory- and a pilot-scale turbulent coal flame.

2 Materials and methods

In this section, the basic concepts of the proposed method are presented, along with the hardware and optical setup used for experiments.

2.1 Image analysis

To analyze shadow images, a Matlab-based software framework was realized. The analysis of shadowgraphs usually consists of detecting dark objects on bright background (particle shadows), computing geometric properties of these objects and object matching. Object matching is a process in which object pairs in consecutive image frames are found and from their displacement their velocities are computed. Because of this, shadowgraphy is capable of providing three distinct properties of the detected objects simultaneously: size, shape and velocity. Size can be defined as the objects equivalent diameter or area. Shape is practically defined as the eccentricity of the objects, which is a parameter that has a value of 1 if an object is a line segment and a value of 0 if an object is a perfectly circular - objects of arbitrary shapes produce values between the two extremes. Model-based techniques have been able to measure particle size and velocity in coal flames, but only separately, i.e., two independent probability distribution functions were obtained - one describing size and one describing velocity. With shadowgraphy, trivariate probability distributions can be obtained, describing the coupled shape, size and velocity behavior of particles. To the best of our understanding, shape parameters of burning coal particles have not been measured systematically before in larger-scale reacting flows. Another advantage of shadowgraphy over laser-based methods is the retaining of a projected particle position. Since the depths of field are typically very shallow in shadowgraphy, particle positions can be closely approximated in the imaged slice.

The image processing software framework consists of a detection module, a matching module and a refinement module. These modules can interact with each other, but can be set up and fine-tuned independently. The detection module is responsible for providing a robust and abundant set of object candidates. The main engine of the detection module uses maximally stable extremal regions (MSERs) as features. The MSER detection routine can be fine-tuned to specific image sets. Detected MSERs can be overlapping features and they are invariant to intensity variations either in the background or foreground. Normally, the detection routine passes the set of detected MSERs to the matching module. By default, the matching module finds maximally correlated monogenic phase patterns in consecutive image pairs by taking the centroid coordinates of the MSERs as input. The refinement module can be used in series either after the detection step or after the matching step. Its main purpose is to eliminate low-contrast objects from the set of object candidates and to remove duplicates caused by overlapping MSERs. The refinement module uses crisp, user-set rules for object classification by default, but it also has capabilities for using fuzzy rules or supervised learning algorithms to achieve the same goal. For further information on how
MSER detection and monogenic phase matching work, please refer to [25, 26]. For processing the image sets presented in this paper, a detection-refinement-matching chain has been used with a refinement criteria system obtained by support vector machines (SVM), a supervised machine learning tool [27]. In brief, SVM is a binary classifier that classifies data in high-dimensional feature spaces. For our application, the soft-margin version of SVM was used with non-linear radial basis functions. This allowed our separating hyperplanes to be curved surfaces and made classification more robust by allowing mislabeled datapoints. The purpose of SVM models was to classify identified image features as either background or objects.

After the detection, refinement and matching steps the object properties were stored in a Matlab structure array. The stored properties are the following: object area, object perimeter, object orientation, object diameter, object centroid coordinates, best fit ellipse axes lengths and displacement coordinates. Since each entry in the structure array corresponds to a detected object (i.e. particle), a true simultaneous measurement of the above properties was possible.

2.2 The combustion systems

Two different sets of equipment were used for experiments of two different scales. The two scales were represented by a laboratory pulverized-coal burner with an approximate heat output of 0.1 kW and a pilot-scale oxycoal combustor with a heat output of 100 kW. The two systems produce approximately 0.1 and 1.5 m long flames, respectively.

The laboratory-scale burner was a laminar pulverized-coal burner with an ethylene pilot flame. Typical flame velocities were around 2 m/s in this flame. This burner was fired with atmospheric air. The pilot-scale oxycoal burner was an axial burner with no swirl, producing a turbulent flame with typical velocities of 10 m/s.

Both systems fired Utah Skyline bituminous coal for the duration of the experiments.

The laboratory-scale burner was confined in an acrylic box in order to reduce atmospheric interference. Small holes were cut in the acrylic as observation ports, thus the shadow images of the laboratory-scale flame were completely unobstructed. The pilot-scale flame was confined in a furnace with refractory walls and steel outer shell. Quartz observation windows were installed for the light source and camera, thus the shadowgraphs of this flame were obstructed by both quartz windows. Soot and dust deposits building up on the windows were blown off periodically by compressed air.

2.3 Optical setup

A high-speed, high-power LED driver with a red (650 nm) emitter, along with a Photron APX-RS type high-speed video camera was used for the laboratory-scale experiments. For the pilot-scale tests a Lavision Imager Pro X 4M type PIV camera and a diffuse laser light source was used. The laser-powered diffuser light source was necessary to overcome the obscuration of the relatively thick flame. Furthermore, the shorter pulse duration of the diffuse light source (20 ns versus the 1 microsecond of the LED) allowed for imaging particle shadows that were moving at higher velocities.
An Infinity K2/SC type long-range, high magnification microscope was used for both experiments as an imaging lens. A sketch of the optical setup is shown in Figure 1.

Along with the optical equipment, heat shields were mounted on the optical rail holding the camera and long-distance microscope in order to avoid damage caused by excessive radiation from the observation windows installed on the pilot-scale furnace. The heat shield was made of a reflective material. A small window was cut on the heat shield in front of the lens. This window was covered with a bandpass filter that only passed the yellow light (560 nm) of the diffuser through. The surface of the bandpass filter facing the flame along with the casing of the diffuser lens was also covered with reflective coating. A Fresnel lens was used to focus the diffused laser light. The temperature of this lens was monitored during the experiments in order to avoid cracking of melting.

3 Results

Since the identification of particles are based on supervised learning concepts, the user is required to complete a training set before using the developed software for batch-processing a real image set. A training set is simply a reduced size image set taken with the same imaging conditions as the image set to be analyzed. The purpose of the training set is to set up the support vector machine model that is used to classify identified image features. Setting up the training set means going through a number of images from which the software proposes randomly selected features as either objects or background. The user manually selects if the proposed decision regarding the image feature being either class is correct or false. Thus, the software is ‘taught’ how to classify identified objects in a supervised manner.

Training sets are therefore labeled, multi-dimensional feature spaces. By labeled, we mean that every data point in the feature space has an additional binary property that identifies it as either background or object. Training sets can be visualized by taking two-dimensional slices in them. An example of such visualization is shown in Figure 2.

Note that the classification shown in Figure 2 is only a two-dimensional slice of a multi-dimensional
Figure 2: A possible visualization of a training set. The feature descriptors displayed here are the intensity and edge gradient magnitude of image features. Crosses denote objects ('yes' decisions) and X symbols denote image features identified as either background or off-focus objects. Colors show the fit SVM model - hues of red denote positive values indicating 'yes' decisions, while hues of blue indicate 'reject' decisions. The decision boundary is shown by the black contour. This model was computed by using a Gaussian basis function.

The success of the phase congruency feature can be explained by the fact that it is an 'intensity-invariant edge feature', meaning that the absolute value of the phase congruency feature is not affected significantly by the gradient magnitude. Thus, inhomogeneous background or partial obscuration as shown in Figure 3 does not hinder the identification of in-focus particles much when using the phase congruency feature. The background inhomogeneity shown in Figure 3 was caused by a passing soot cloud in the pilot-scale flame.

Another parameter that may be included in the feature spaces of the SVM models is the difference
Figure 3: The effect of including the edge phase congruency measure in particle identification. The top row shows three-dimensional cross-sections of the fit models. The bottom row shows corresponding identifications in the same pilot-scale image frame. Note how including the phase measure resulted in the more satisfactory identification of partly obscured particles. The model visualizations show plots of the particle shape factor ($C$), edge gradient magnitude ($\nabla$), edge phase congruency measure ($\Psi$) and object size ($d$). Feature descriptors are normalized. Decisions boundaries are shown by gray surfaces. Particles in the training sets are denoted by green spheres, while non-particle decisions are shown by red spheres. Identified particles are denoted by green contours.

of particle displacement relative to an a priori available displacement value. The computation of such an a priori displacement field is possible by using conventional PIV or optical flow algorithms (e.g., as described in [28]). Naturally, the training sets including such a parameter would be defined between subsequent image frames and would result in an identification scheme that is closer to true Bayesian decision making. The graphical interface for setting up such training sets was completed at the time of the submission of this paper, but results of the evaluation of the concept were not available. Figure 4 shows the results of each step of the general methodology.

To test the accuracy of particle identification, we carried out a number of experiments using glass bead particles instead of coal. The diameters of glass beads were known a priori and we also measured them with a laser-scattering particle sizer. A mixture of two different sizes were used, mixed with a known mass fraction. The results of particle sizing are shown in Figure 5.

As Figure 5 shows, shadowgraphy proved to be a more accurate method for sizing than laser-scattering. The theoretical size distributions are closely approximated by both SVM models. Non-
zero frequencies found between the two realistic peaks correspond to overlapping particles with intermediate apparent diameters. The evaluation of these experiments were done by computing the ratio of occurrences in the two size fractions. The theoretical mixing ratio was 1.034. Laser-scattering sizing produced a ratio 0.629, while shadowgraphy yielded values of 1.13 and 1.016, respectively.

At the time of the submission of this work, the experiments on the pilot-scale flame were still under progress, thus for the balance of this paper, examples from the results obtained from the study of the laboratory-scale flame are shown. Figure 6 shows extracted particle size and particle velocity histograms from images of the laboratory-scale flame.

Figure 6 well illustrates the significant effect of altering the fuel-air equivalence ratio in the studied flame. While flames with both equivalence ratios showed similar particle size distributions close at the burner surface, the distributions became quite different in them further away from the burner. The fired pulverized coal was a size-separated fraction between 70 and 90 µm. The fuel-lean flame ($\phi = 0.25$) produced slightly bimodal particle size distributions above HAB=40 mm. The coarser fraction corresponds to particles formed during pyrolysis. These particles were very elongated, thus the reasonably large diameters. The finer fraction corresponds to particles formed by the breakup of the elongated particles. Velocities generally increased with HAB. The fuel-lean flame produced faster moving particles in higher regions.
Figure 5: Results of the sizing of glass beads particles. This figure shows obtained particle size distributions with laser-scattering sizing (LS) and two different SVM models (named ‘area’ and ‘model’). The theoretical distribution was computed based on the mixing ratio of the two size fractions and the size guaranteed by the manufacturer.

Figure 6: Results obtained from shadowgraphs of the laboratory-scale flame. Particle size and particle velocity histograms are shown. Rows indicate heights above burner (HAB). Two different fuel-air equivalence ratios were used to produce the flames, $\phi = 0.92$ and $\phi = 0.25$. 
4 Conclusion

This paper presents a novel image analysis framework for the quantitative shadowgraphy of coal flames. Quantitative shadowgraphy combines digital image processing with shadow imaging and is capable of measuring joint distributions of particle size, shape, velocity and position in reacting flows. A solution for the problem of processing degraded and busy images of dense reacting flows was proposed. The capabilities of this new method were demonstrated by using shadow images of a pilot-scale and laboratory-scale pulverized coal flame.

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References


