



Flame four-dimensional deflection tomography with compressed-sensing-revision reconstruction



Bin Zhang*, Minmin Zhao, Zhigang Liu, Zhaohang Wu

College of Electromechanical Engineering, Qingdao University of Science and Technology, Qingdao 266061, China

ARTICLE INFO

Article history:

Received 16 June 2015

Received in revised form

1 January 2016

Accepted 28 February 2016

Available online 22 March 2016

Keywords:

Deflection tomography

Four-dimensional visualization

Premixed combustion

Array projection sampling

Reconstruction algorithm

ABSTRACT

Deflection tomography with limited angle projections was investigated to visualize a premixed flame. A projection sampling system for deflection tomography was used to obtain chronological deflectogram arrays at six view angles with only a pair of gratings. A new iterative reconstruction algorithm with deflection angle compressed-sensing revision was developed to improve reconstruction-distribution quality from incomplete projection data. Numerical simulation and error analysis provided a good indication of algorithm precision and convergence. In the experiment, 150 fringes were processed, and temperature distributions in 20 cross-sections were reconstructed from projection data in four instants. Four-dimensional flame structures and temperature distributions in the flame interior were visualized using the visualization toolkit. The experimental reconstruction was then compared with the result obtained from computational fluid dynamic analysis.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Flows encountered in combustion and fluid dynamics involve complex interactions of physical and chemical processes. Presently, visualization and quantitative measurements of important combustion parameters, such as temperature, concentration, velocity, rate of heat release, and pollutant emission, are common tools of the combustion scientist and engineer. Optical and laser diagnostic techniques use a large number of advanced instruments, which provide continuous or high-speed measurements with high spatial resolution, flow-stopping interrogation times, and advanced strategies for quantitative calibration [1,2]. These diagnostic techniques are also useful for the measurements of complex flow fields, including coherent anti-Stokes Raman scattering, cavity ring-down spectroscopy, degenerate four-wave mixing, laser-induced breakdown and grating spectroscopy, laser-induced fluorescence and incandescence, laser Doppler velocimetry, phase Doppler anemometry, particle imaging velocimetry, Raman and Rayleigh scattering, and resonance-enhanced multiple photon ionization [3]. Moreover, optical and laser diagnostic techniques rely on scattering, absorption, and emission techniques; linear and non-linear approaches; and one- or multiple photon schemes, to characterize temperature, velocity, concentrations, and their local gradients or spatial and temporal variations. Distinguishing

features may include single-point detection and multi-dimensional imaging, detection of emission from tracer molecules and seed particles, pump-probe, double-pulse approaches, and grating schemes. Alternatively, optical tomographic techniques have been used in fluid flows with absorption, optical phase, and deflection measurements. Optical tomography methods have significant advantages in visualization and parameter diagnosis of complex flow fields, hence making it easier to determine that the actual measured object is a mixed flow field when complex combustion flows into air [4–8]. Absorption techniques [9–13], with computed tomography tunable diode laser absorption spectroscopy, frequency-agile tomography, and multiplexed absorption tomography, measure the decrease in the intensity of light ray, following the passing through the medium. Consequently, this change in intensity can be related with the physical properties of the medium. In interferometry [14–16], coherent light rays passing through the medium are combined with respective reference beams to form a fringe pattern. The interference pattern can be interpreted quantitatively by measuring the fringe spacing that is related with the refractive index of the medium. Deflectometry has been used with Ronchi gratings placed before the decollimating lens. Gradients in the medium deform the moiré pattern, such that the displacement of a fringe is proportional to the local beam deflection. Deflection tomography with moiré technology is known for simple devices, large dynamic range, and low requirement for mechanical stability; this technique is also suitable for the measurements of high-temperature and high-speed flow fields [17–19].

* Corresponding author. Tel.: +86 13156289096.

E-mail address: zb-sh@163.com (B. Zhang).

Deflection tomography comprises two major steps in reconstructing three-dimensional refractive index fields. First, multi-directional deflection projections are experimentally captured. Second, the data are numerically processed with computational tomographic algorithms for reconstruction from projections.

To date, various experimental configurations to obtain field projections have been reported including rotation of the object field or probing beam and spatial or temporal cascade division and redirection of the probing beam. These approaches exhibit both merits and shortcomings. The object or beam rotation scheme is simple [19,20], but does not allow accurate instantaneous capture of a field. The beam division approach can provide only a limited number of projections because of complexities that may arise given that the setup has to be duplicated to obtain each projection [21]. Computational reconstruction techniques can be classified into transform and series expansion methods. The algebraic reconstruction technique (ART), the most famous series expansion method, allows for direct computational reconstruction from a limited data set, which may provide a restricted view, a limited number of projections, or incomplete projections as a result of the presence of an opaque object [22,23]. Song et al. presented a novel algebraic iterative algorithm based on deflection tomography. This algorithm was derived from essentials of deflection tomography with a linear expansion of local basis functions, and has been used in a series of complex flow field measurements [24].

With the development of new combustion technologies and combustors, visualization of flame structure and measurement of transient combustion parameters have become hot research topics [25,26]. However, the existing deflection tomography technology is not competent for instantaneous flow field measurements. The beam duplication approach does not ensure exact replicability of a beam path, resulting in substantial increase in measurement error. The available inversion algorithm is not inadequate in the deflection tomographic reconstruction of instantaneous complex flow field from sparse projections.

This research draws inspiration from an array of individual mirrors in the digital micromirror device (DMD) [27,28]. The DMD mirror is an opto-mechanical element in that two positions determine the direction where light is deflected. In particular, the DMD is a spatial light modulator. With the principle of the mirror array in DMD, a deflection tomographic setup is presented to obtain the chronological arrays of multidirectional deflectograms. Deflection projections in different view-angles can be captured synchronously in the same optical path condition by a CCD camera. Theory of compressed sensing (CS) enables accuracy reconstruction from few view-angle projections in inversion algorithm. CS is a new rapidly growing research field that has already become a key concept in various areas of applied mathematics, computer science, and image engineering [29–31]. CS allows for recovery of a sparse signal from very few non-adaptive, linear measurements by convex optimization. Based on the CS theory, an algorithm is derived for deflection tomographic reconstruction from incomplete projection data. Subsequently, four-dimensional unstable state flow field can be measured with the new deflection tomography technology and visualized using the visualization toolkit (VTK). Section 2 describes the derivation of the reconstruction algorithm and demonstrates the efficacy of the proposed algorithm using numerical simulated data. In Section 3, a projection array sampling system is introduced; four-dimensional measurements and visualizations of premixed combustion are also carried out. Section 4 summarizes the results obtained.

2. A tomographic reconstruction algorithm with deflection angle CS revision

2.1. Discretized representation of CT reconstruction

A ray bends when passing through a phase object along the x -direction because of the refraction associated with the refractive index gradient of the object. The ray deflection angle φ in the y -direction within the paraxial approximation is given by integral along the phase object:

$$\varphi \approx \int_{-\infty}^{\infty} \frac{1}{n_0} \frac{\partial n(x,y)}{\partial y} dx, \quad (1)$$

where $n(x,y)$ is the refractive index associated with the two-dimensional phase object at a point (x,y) . The reconstruction domain is digitized into $w \times w$ grids. A constant value of the distribution is assumed to be n_i on each grid. The grids are numbered from 0 to $k-1$, and the sides of the grids have a length d . Supposing l represents the number of projections and m is the number of samples per projection, the deflection angle associated with the j th ray φ_j should satisfy the following:

$$\sum_{i=0}^{k-1} A_{ij} \left(\frac{1}{n_0} \frac{\partial n_i}{\partial y} \right) \approx \varphi_j \quad j=0, \dots, (m-1) \times l, \quad (2)$$

where A_{ij} is the length of the intersection of the j th ray with the i th grid and n_0 is the refractive index of the surroundings.

2.2. Iterative reconstruction algorithm with CS revision

The partial derivative $\partial n_i / \partial y'$ can be calculated using four-neighbors algorithm depicted in Fig. 1. With a series of derivation, Eq. (2) can be written as a linear equation as follows [19–20]:

$$\mathbf{Dn} = \mathbf{Cn} - \mathbf{h} + \mathbf{q}, \quad (3)$$

where

$$C_{ij} = K \frac{A_{(i+1)j}}{d} + \frac{A_{(i-w)j}}{d}, \quad (4)$$

$$D_{ij} = K \frac{A_{(i-1)j}}{d} + \frac{A_{(i+w)j}}{d}, \quad (5)$$

$$q_j = n_0 \left(\frac{\sum_{top} A_{ij} - \sum_{bottom} A_{ij}}{d} + K \frac{\sum_{left} A_{ij} - \sum_{right} A_{ij}}{d} \right), \quad (6)$$

$$h_j = 2n_0 \varphi_j \sqrt{1+K^2}. \quad (7)$$

In Eqs. (4)–(7), K is the slope of the incident ray with respect to the horizontal direction and the subscripts *top*, *bottom*, *left*, and *right* denote the grids on the four sides of the reconstructed square region, as shown in Fig. 1. The ray trajectory is calculated to obtain A_{ij} in an inhomogeneous field. A ray is refracted following Snell's law upon meeting a neighboring element at point M, as shown in Fig. 2. In digital ray-tracing on a computer, the forward process may be calculated by stepping through the object plane from the refractive index values on different square lattices.

CS-based reconstruction algorithms have attracted a great deal of attention for CT applications with limited number of projections. The main premise of CS is that, although the signal is not necessarily sparse in real space or Fourier space, it is sparse or compressible in some basis. According to the CS theory, the sparse property of the gradient distribution can be used in the reconstruction. For instance, the l_1 norm of the gradient distribution can be used as the objective function to be minimized; that is, the so-called distribution total variation (TV) minimization method. The

Download English Version:

<https://daneshyari.com/en/article/7132282>

Download Persian Version:

<https://daneshyari.com/article/7132282>

[Daneshyari.com](https://daneshyari.com)