
THERMAL PARTICLE IMAGE VELOCITY ESTIMATION OF FIRE PLUME FLOW

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For the purpose of studying wildfire spread in living vegetation such as chaparral in California, a thermal particle image velocity (TPIV) algorithm for nonintrusively measuring flame gas velocities through thermal infrared (IR) imagery was developed. By tracing thermal particles in successive digital IR images, the TPIV algorithm can estimate the velocity field in a fire-plume flow. In this method, the thermal particle is assumed to be a virtual particle that corresponds to the “hot” pixel resolved in a digital image. Its signal is a temperature value measured by a thermal IR camera. Fire-plume experiments using alcohol and chamise (*Adenostoma fasciculatum*) as fuels and a computational simulation have been completed. A thermal IR camera was used to

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capture successive fire temperature images. Using these images, velocity fields were estimated by the TPIV algorithm. For numerical simulation, the computed detailed instantaneous velocity field was used to validate the field estimated by the TPIV algorithm. Results illustrate the applicability and performance of the TPIV algorithm in fire research.

Keywords: fire, velocity, temperature, TPIV

INTRODUCTION

Wildfire spread in living vegetation such as chaparral in California, coniferous forests throughout much of North America, and eucalyptus forests in Australia often causes significant damage to infrastructure and ecosystems. For predicting fire spread rate, existing operational models utilized by the Forest Service are based on the semiempirical model developed originally by Rothermel (1972). It is applicable to quasi-steady burning of surface fires with uniform fuel loading and assumes that the fuel is dominated by dead material and in close proximity to the ground. Crown fire, transition from ground to crown fire, fire spread through live fuels, fire spread by spotting, and modification of meteorological conditions by the fire are some of the phenomena not accounted for in the Rothermel model. Wilson (1982, 1985, 1990) suggested addition of a term in the spread model involving wind and fuel moisture. Albini studied fire spread in brush and presented a model for radiation-dominated wildfire spread (Albini, 1967, 1985, 1986, 1996; Albini and Stocks, 1986). However, the application of this to shrub fuel beds such as chaparral is currently unknown. Fuel depths observed in chaparral crowns range from 30 to 120 cm and vary by species, elevation, slope, and rainfall. Total height of chaparral stands ranges from 1 to 6 m, and the crowns tend to be fairly porous (low packing ratio). In fact, fire spread in chaparral has been described as a crown fire. This provides the motivation to determine what is necessary to establish a propagating flame front in chaparral brush fuels, independent of ground fuels.

Fire spread in wildland fuels is created by the coupled effects of fuel combustion, air convection, flame and ember radiation, and mechanical advection effects such as rolling embers and spotting. As an essential component of the convection, intense fire vortices on the scale of meters almost certainly play a fundamental role in the physics of fire spread (Byram and Martin, 1970; Emmons and Ying, 1967; Haines, 1982). McRae and Flannigan (1990) describe fire vortices that in one case

were observed to rip out and loft standing trees. Clark et al. (1999) observed a fire vortex rising more than 3 km above ground level with flaming materials that were visible at about 2 km. Therefore, fire vortices not only are suspected of being hazards to nearby firefighters, but are an important fire spread mechanism through both local dynamics and the ability to loft flaming objects into areas well removed from the former fire front (Clark et al., 1999). Because of the difficulty in measuring the velocity field in a wildfire, there is no currently available data that describes the small temporal and spatial scales involved in the fire vortices that help to determine fire spread.

The focus of this article is on the investigation of nonintrusive techniques for measuring flow velocities within the vicinity of a flame using digital radiant temperature images obtained by a thermal infrared (IR) camera. Because the wavelengths of thermal emissions are in the IR range between 3 and 15 μm , and thermal emission is proportional to the fourth power of surface temperature, IR cameras have been used successfully to detect and map temperature field within wildfires. With increasingly sensitive image converters and improvement of software, high-resolution and high-frequency digital IR images are available now and offer some useful advantages to fire researchers. One of these advantages is that a number of physical mechanisms contributing to the fire spread rate may be investigated using image flow analysis. The velocity field that represents the motion of object points across an image is called the optical flow field. Optical flow results from relative motion between a camera and objects in the scene. One method of estimating flow velocities is the "gradient-based algorithm," which relies on an equation that relates optical velocities to spatial and temporal changes in the image (Brandt, 1997; Kearney et al., 1987). The general assumption in this algorithm is that the gradient of the image signal is stationary (conserved) over a short time. Using this method, Clark et al. (1999) derived a dataset from a prescribed burn during the International Crown Fire Modeling Experiment. They found that the motions during the crown fire had energy-containing scales on the order of meters with timescales of fractions of a second. The enhanced tilting of horizontal vortices led to counterrotating convective towers with estimated vertical vorticities of 4 to 10 s^{-1} rotating such that air between the towers blew in the direction of fire spread at canopy height and below.

Following the work of Clark et al. (1999) on gradient-based algorithms, an alternate method is developed in this article to estimate velocity using the idea established in particle image velocimetry (PIV; Raffel et al., 1998; Willert and Gharib, 1991). The PIV method allows evaluation of the instantaneous velocity field by recording the position of seed particles at successive time images. In our method, the seed particles are represented by thermal particles in IR images, where thermal particles are assumed to be virtual particles that correspond to the "hot" pixels resolved in digital images. The signal from a thermal particle is a temperature value measured by an IR thermal camera. It is assumed that thermal particles rotate and translate, behaving like a fluid particle, and their temperatures are conserved over a short time required for analysis. Following this, a thermal particle image velocity (TPIV) algorithm is developed to estimate the flow velocities in the buoyant fire plume. The technique adopted is similar to that of Clark et al. (1999).

Experiments were completed using alcohol and live chamise as fuels. Chamise (*Adenostoma fasciculatum*) is one of the most hazardous wildland fuels in southern California. Temperature images were acquired by an FLIR ThermoCAM SC500¹ with an uncooled microbolometer 320×240 pixel focal plane array sensitive to the 7.5- to 13- μm spectral range. Results from application of the TPIV algorithm to estimate fluid velocities are presented. To validate the estimated velocities, a measured instantaneous velocity field is needed. However, measuring instantaneous values of velocity in a fire is generally difficult because physical probes with fast time response often cannot survive in the high gas temperatures in the fire. Some techniques are available, such as the ingenious correlation probe used by Cox and Chitty (1980, 1985), but may not always accurately define the direction of the measured amplitude. The use of Laser Doppler Velocimetry (LDV) measurement techniques is difficult because seeding the fuel, or the air, or both does not properly weigh the signals from hot or cold gas. The use of bidirectional probes (McCaffrey and Heskestad, 1976) is being examined to measure flame velocities.

As a useful validation tool, a computational fluid dynamics (CFD) code was utilized to simulate the fire plume for conditions approximating the laboratory experiments. The advantage of a validated CFD code is that the detailed temperature and velocity field at each time step can be

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obtained. If the predicted temperature fields are approximated as the IR thermal images, we can estimate the fluid velocity fields using these temperature images through the TPIV algorithm. Our goal is to validate the TPIV algorithm by comparing these estimates with predicted velocities. In this article, the fire dynamics simulator (FDS) code developed by McGrattan et al. (2000) was used to compute the temperature and velocity field in the fire plume. Results illustrate the applicability and performance of TPIV algorithm in fire research.

THERMAL PARTICLE IMAGE VELOCITY (TPIV) ALGORITHM

The TPIV algorithm requires at least two successive temperature images taken at two different time levels to calculate velocity field. Figure 1 illustrates a patch of two temperature images obtained from numerical simulation of a buoyant fire plume. The time difference is 0.00687 s. Each image includes 11×11 grid points and the center point, denoted by a black filled circle with coordinates (x, z) , is considered for analysis. Here x and z denote horizontal and vertical coordinate directions in the image. The signals at these grid points are temperature values calculated from numerical simulation code or measured by thermal IR camera. In the TPIV algorithm, these grid points with temperature as signals are approximated as thermal particles that correspond to seed particles in a PIV method, which in turn approximate fluid particles. As seen in Figure 1,

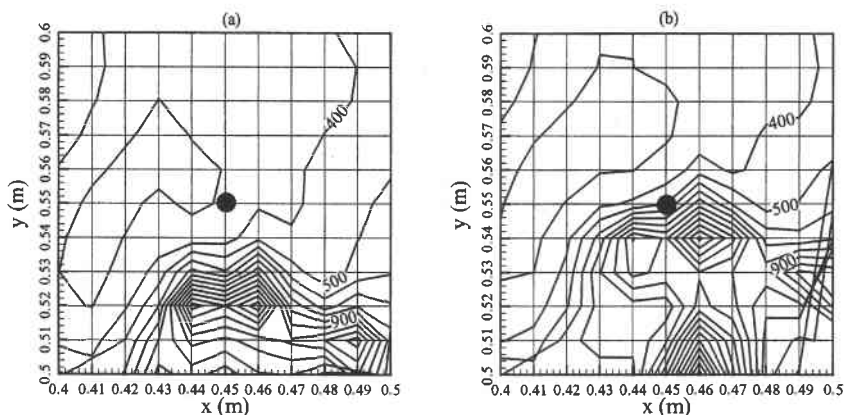


Figure 1. Movement of temperature contours of a fire plume in a time difference of 0.00687 s. A patch of 11×11 grid points is shown.

because of the prime updraft fire flow, the temperature contours move upward with the fluid flow and the shape stays almost unchanged over the short time.

By assuming that thermal particle motion is dominated by pure translation, each of the thermal particles of frame 1 translates from coordinate (x, z) to $(x + \Delta x, z + \Delta z)$ of frame 2 over a short time interval Δt with speed u and w , where u and w are velocity components along x - and z -directions. If the signals of the thermal particles are conserved over this short time, the function that we want to minimize is of the form

$$\Lambda = \sum [\phi_2(x + \Delta x, z + \Delta z) - \phi_1(x, z)]^2 \quad (1)$$

where ϕ_1 is the temperature at time t , and ϕ_2 is that at time $t + \Delta t$. The summation is taken over a patch of grid points in the image. The patch size of thermal particles may be 11×11 (shown in Figure 1) or any other desired value that depends on the sampling rate of temperature images. The smaller rate requires bigger patch size in order to obtain enough information from the data. Using a Taylor series expansion, ϕ_2 is approximated as

$$\phi_2(x + \Delta x, z + \Delta z) = \phi_2(x, z) + \Delta x \phi_x + \Delta z \phi_z \quad (2)$$

where ϕ_x and ϕ_z are the partial derivatives of ϕ along x and z , respectively. The derivatives can be estimated using a finite difference scheme. By substituting Eq. (2) in Eq. (1), the quantity Λ is minimized with respect to Δx and Δz . This results in the matrix equation for the estimate of Δx and Δz :

$$\begin{bmatrix} \sum \phi_x^2 & \sum \phi_x \phi_z \\ \sum \phi_x \phi_z & \sum \phi_z^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta z \end{bmatrix} = \begin{bmatrix} \sum (\phi_1 - \phi_2) \phi_x \\ \sum (\phi_1 - \phi_2) \phi_z \end{bmatrix} \quad (3)$$

Once Δx and Δz at each grid point are calculated, velocity components u and w at each grid point can be calculated from

$$u = \frac{\Delta x}{\Delta t} \quad w = \frac{\Delta z}{\Delta t} \quad (4)$$

respectively.

In the more generalized case thermal particles are generally allowed to undergo both translation and rotation at the same time. Assuming first that fire motion is pure rotation, define (x_1, z_1) to be coordinate of frame 1 and (x_2, z_2) to be that of frame 2, which has been purely rotated from frame 1. Based on the Cartesian coordinate transformation,

$$\begin{bmatrix} x_2 \\ z_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_1 \\ z_1 \end{bmatrix} \quad (5)$$

where θ is the angle of rotation. Then pure translation is added:

$$\begin{bmatrix} x_2 \\ z_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_1 \\ z_1 \end{bmatrix} + \begin{bmatrix} \Delta x_2 \\ \Delta z_2 \end{bmatrix} \quad (6)$$

where Δx_2 and Δz_2 denote translation in frame 2. The expression for Δx and Δz is

$$\begin{bmatrix} \Delta x \\ \Delta z \end{bmatrix} = \begin{bmatrix} x_2 - x_1 \\ z_2 - z_1 \end{bmatrix} = \begin{bmatrix} \cos \theta - 1 & \sin \theta \\ -\sin \theta & \cos \theta - 1 \end{bmatrix} \begin{bmatrix} x_1 \\ z_1 \end{bmatrix} + \begin{bmatrix} \Delta x_2 \\ \Delta z_2 \end{bmatrix} \quad (7)$$

For small value of θ , using a Taylor series extension of $\cos \theta = 1 - \theta^2/2! + \theta^4/4! - + \dots$ and $\sin \theta = \theta - \theta^3/3! + \theta^5/5! - + \dots$, the quantity $(\cos \theta - 1)$ can be approximated as $(-\sin^2 \theta)/2$ by dropping higher order terms:

$$\begin{bmatrix} \Delta x \\ \Delta z \end{bmatrix} = \begin{bmatrix} -\sin^2 \theta/2 & \sin \theta \\ -\sin \theta & -\sin^2 \theta/2 \end{bmatrix} \begin{bmatrix} x_1 \\ z_1 \end{bmatrix} + \begin{bmatrix} \Delta x_2 \\ \Delta z_2 \end{bmatrix} \quad (8)$$

Using Taylor series expansion for $\phi_2(x + \Delta x, z + \Delta z)$, the quantity Λ is minimized with respect to three dependent variables: $\sin \theta$, Δz_2 , and Δx_2 . The resulting matrix equation after minimizing Λ is

$$\begin{bmatrix} A & D & E \\ D & B & F \\ E & F & C \end{bmatrix} \begin{bmatrix} \sin \theta \\ \Delta z_2 \\ \Delta x_2 \end{bmatrix} = \begin{bmatrix} G \\ H \\ I \end{bmatrix} + \begin{bmatrix} R_1 \\ R_2 \\ R_3 \end{bmatrix} \quad (9)$$

where the coefficients are the following:

$$A = \sum (-y\phi_x + x\phi_y)^2 \quad (10)$$

$$B = \sum \phi_y^2 \quad (11)$$

$$C = \sum \phi_x^2 \quad (12)$$

$$D = \sum (y\phi_x\phi_y - x\phi_y^2) \quad (13)$$

$$E = \sum (-x\phi_x\phi_y + y\phi_x^2) \quad (14)$$

$$F = \sum (\phi_x\phi_y) \quad (15)$$

$$G = \sum (\phi_1 - \phi_2)(y\phi_x - x\phi_y) \quad (16)$$

$$H = \sum (\phi_1 - \phi_2)\phi_y \quad (17)$$

$$I = \sum (\phi_1 - \phi_2)\phi_x \quad (18)$$

$$R_1 = \sum (x\phi_x + y\phi_y)(y\phi_x - x\phi_y) \sin^2 \theta/2 \quad (19)$$

$$R_2 = \sum (x\phi_x + y\phi_y)\phi_y \sin^2 \theta/2 \quad (20)$$

$$R_3 = \sum (x\phi_x + y\phi_y)\phi_x \sin^2 \theta/2 \quad (21)$$

where the summation is taken over a patch of grid points.

In the numerical calculation, a local coordinate system is set up around a patch of grid points. As seen in Figure 1, the coordinate of the center point (x, z) is chosen to be $(0, 0)$. Then the displacement Δx and Δz of the thermal particle can be approximated as Δx_2 and Δz_2 or calculated approximately by the following relation:

$$\begin{bmatrix} \Delta x \\ \Delta z \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} \Delta x_2 \\ \Delta z_2 \end{bmatrix} \quad (22)$$

Given the final estimates of Δx and Δz , velocity components u and w at each grid point can be calculated by Eq. (4). In our numerical calculation, three successive temperature images are utilized. The displacements Δx and Δz between images 1 and 2, and between images 2 and 3, are calculated by TPIV algorithm, respectively. Averaged values ($\overline{\Delta x}$, $\overline{\Delta z}$) and velocity fields in the center image 2 are obtained. In other words, it calculates the average velocities within a time difference but not instantaneous velocities of each image itself.

FIRE-PLUME EXPERIMENT

Experiments were performed on small fires in the middle of the fire laboratory, which is a $12\text{ m} \times 12\text{ m} \times 7.6\text{ m}$ (H) unconditioned building well away from aerodynamic obstacles. Two fuels, alcohol and chamise (*Adenostoma fasciculatum*), were used in the fire-plume experiments. Alcohol is a liquid fuel, readily available in the laboratory. Compared to live shrub fuel of chamise, the burning condition of the alcohol pool fire is more simple, stable, and easy to control; the burning rate is uniform. For the use of computer simulation, these are also suitable conditions. However, our main purpose is to study wildfire spread and to develop a relatively inexpensive method of estimating fluid velocities in the vicinity of the fire. Therefore, the TPIV algorithm was also used to estimate the gas velocity in the fire plume of chamise.

For alcohol, the small fires were contained in a steel pan with diameter of 0.177 m and depth 0.04 m. Because chamise is a solid porous fuel, the experimental setup was more complicated. Chamise is a common, aggressive shrub that grows in pure stands or in mixture with other chaparral species in the mountains and foothills of California. It is one of the most hazardous wildland fuels (Countryman and Philpot, 1970). In the present experiment, live branches and foliage with diameter up to 6.3 mm were used. Foliage was retained on the branches. Branches were cut from living plants in the morning of the experiment so as to minimize moisture loss through transpiration. Dead fuel was removed to the extent possible. The fuel was then bagged and transported to the fire laboratory. A circular steel screen container was designed to contain chamise. To construct the fuel bed, an amount of chamise with a known mass spread uniformly over the container, fluffed on the fuel bed to remove tightly packed concentrations, and lightly and uniformly pressed down to the final fuel bed depth. Extraneous vertical strands above the bed surface

were then clipped. The spacing of individual fuel elements in the fuel bed, or how crowded they are together, may be referred to in terms of packing ratio, or its reciprocal, porosity (Countryman and Philpot, 1970). Packing ratio is defined as the ratio of fuel volume to fuel-bed volume. In this article, the packing ratio (Rothermel, 1972) can be calculated from

$$\beta = \frac{W}{A \cdot \delta \cdot \rho_p} \quad (23)$$

where W is the dry mass of the fuel bed, A is the surface area of the bed, δ is the fuel bed depth, and ρ_p is the fuel particle density. The variables δ and β are both fuel-bed properties that can be controlled. However, the level of control is not as great as in many other laboratory experiments because brush fuels do not tend to be as uniform as dowels, match sticks, excelsior, index cards, and other milled fuels. In this article, the diameter of the container is 0.3 m and the height is 0.2 m. The mean moisture content of the chamise was 53%, typical of measured fuel moistures when large fires with active burning occur in chamise fuels. We assumed chamise density of 715 g/m³ (Countryman and Philpot, 1970). The calculated packing ratio was 0.019.

For the IR-based method, we used successive digital images captured by an IR thermography camera and used thermal tracing to estimate velocity field. An IR thermography camera can produce images of invisible IR or "heat" radiation and provide a precise noncontact estimate of the temperature field. Successive images were captured from the SC500 IR camera, which can provide optimal thermal sensitivity and noncontact temperature measurement precision where thermal differences are small or very high accuracy is desired. Temperature changes as small as 0.07°C can be detected. The maximum sampling rate of the thermal camera is 60 Hz. ThermaCAM software was used to obtain a 320 × 240 pixel temperature field. A default flame emissivity (ϵ) of 0.92 suggested by the IR camera manufacturer was used. Even though the flame emissivities are lower than 0.92, the results presented by the TPIV algorithm are not affected since all pixels in the image were assigned equal ϵ . The TPIV estimates the gas velocities based on the movement of the temperature field in successive IR images, and the assumption is that emissivity does not change over short time intervals between images. At separate points above the pool fire, temperatures were also measured by 24-gauge Type K thermocouples, which are used to estimate ϵ for the various flames we

are studying. An electrical scale was used to measure fuel mass loss with time. A heat flux sensor was used to measure the rate of heat flux. The thermocouple results, the heat flux sensor results, and the electrical scale results are not included in this article.

NUMERICAL COMPUTATION OF FIRE PLUME

The FDS code developed by McGrattan et al. (2000) was used for the computation of fire plume under the approximate conditions of the present experiment. The FDS code solves the low-Mach-number approximate form of the Navier-Stokes equations appropriate for low-speed, thermally driven flows of smoke and hot gases generated in a fire. The approximation involves the filtering of acoustic waves while allowing for large variations in temperature and density. This gives the equations an elliptic character, consistent with low-speed, thermal convective processes (Mahalingam et al., 1990). The computation is treated as a large-eddy simulation in which the large-scale eddies are computed directly and the subgrid-scale dissipative processes are modeled. The fire is represented by discrete Lagrangian particles (or thermal elements) that originate at the burner (or solid surface) and release heat at a specified rate.

McGrattan et al. (1994, 1998) utilized this code to simulate fire plumes under different conditions and obtained results comparable with experiments, thereby validating the code. In this article, the computed temperature data at successive times are approximated as IR thermal images. Our goal is to utilize these predicted temperature data to estimate fluid velocities using the TPIV algorithm, and to validate these estimates by comparison with predicted velocities. For the present computation of the FDS code, a three-dimensional computational domain is used. The size is $0.8 \times 0.6 \times 0.8$ m along the x -, y -, and z -directions, respectively. The grid used is $81 \times 61 \times 81$. The heat-release rate per unit area is 615 kW/m^2 , which approximates the heat release of alcohol pool fire in the experiment. The ambient temperature is 25°C .

RESULTS AND DISCUSSION

Estimated Velocity from Measured IR Images

The thermal IR camera was used to capture the digital temperature images of fire plume using alcohol and chamise as fuels. Based on these

images, the velocity field of the fire plume was estimated by TPIV algorithm. It is important to note the difference between the measured IR temperature image and the calculated temperature field by CFD code. Using a three-dimensional CFD code, we can obtain an exact two-dimensional temperature field at any x - z plane. However, each IR camera temperature image represents an average over a significant depth (in y direction) into the flame front. As a result, the estimated velocity components are representative for similar depth. Apparent motions in the image may contain motions into or out of the image, whereas we estimate only those that project onto the two-dimensional distorted sheet (Clark et al., 1999).

Figure 2 illustrates two successive temperature contours captured by the thermal IR camera over a pool fire of alcohol. The diameter of the steel pan containing alcohol is 0.177 m. Two temperature contours are overlapped and the later one is illustrated as a dashed line. The time difference is 0.0167 s corresponding to a sampling rate of 60 Hz. Over this short time period, a minor upward movement of the temperature fields can be observed, however, with a tilt to the left side.

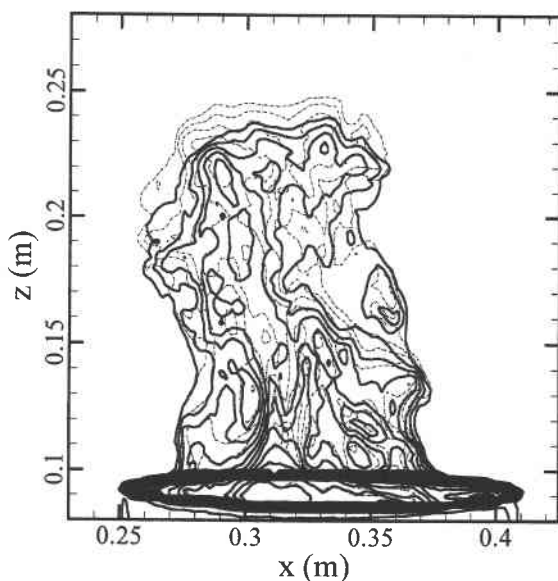


Figure 2. Movement of successive images of temperature contours measured from thermal IR camera for alcohol pool fire plume with a time difference 0.0167 s or sampling rate 60 Hz. The solid line corresponds to the first image and the dashed line is the later one.

The TPIV algorithm with patch size 11×11 was applied to this sequence of temperature images to derive the velocity field. Figure 3 shows the estimated fire velocity vectors overlying the background IR temperature field. At the base region of the fire plume, the estimated velocities are very small. This is because the momentum flux of the pyrolysate is typically very small and the buoyancy forces are still small. However, the directions of velocity vectors illustrate the entrainment of ambient air. Above this region, because of the entrainment of a large amount of air and the increase of the buoyancy forces, the upward velocity vectors and rotating vortices are as shown in Figure 3. There is an accelerating central core in the fire plume and strong rotation at the center and the edge of the fire plume. This is consistent with the vortex observed visually during the experiment. Because each IR image is an average over a significant depth into the flame front, the estimated velocity vectors are also averaged for similar depth. Figure 3 shows an overlap of upward flow and rotation coexisted in a fire plume. It is known that the fire vortex leads to strong radial inflow of ambient air into the

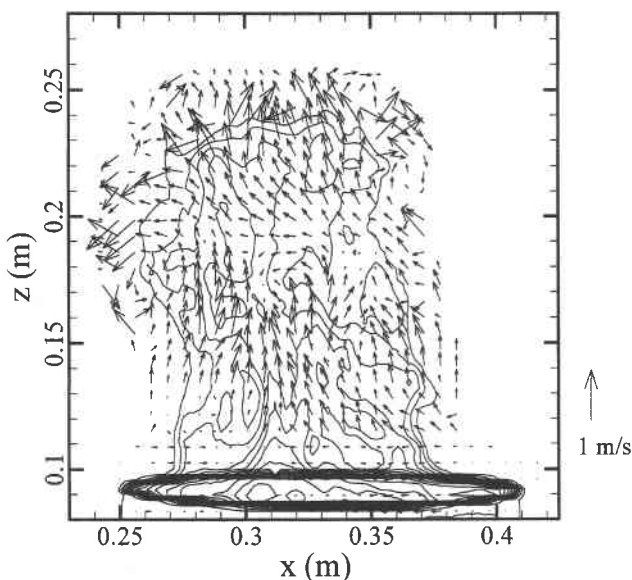


Figure 3. Velocity vector field estimated by the TPIV algorithm using temperature images measured from thermal IR camera for alcohol pool fire plume. Sampling rate is 60 Hz. The patch size is 11×11 . Temperature contours are illustrated to show the flame shape.

core of the fire. The estimated velocity field is useful to describe the small temporal and spatial scale involved in fire vortices that help to determine fire spread. The estimated peak value of vertical velocity is about 0.9 m/s. Overall, the estimated velocity field using the TPIV algorithm appears reasonable.

For the purpose of studying the wildfire spread in living vegetation, such as chaparral in California, we investigated the flow field above a fire plume using live chamise as fuel. Figure 4 illustrates two successive temperature contours captured by thermal IR camera from such an

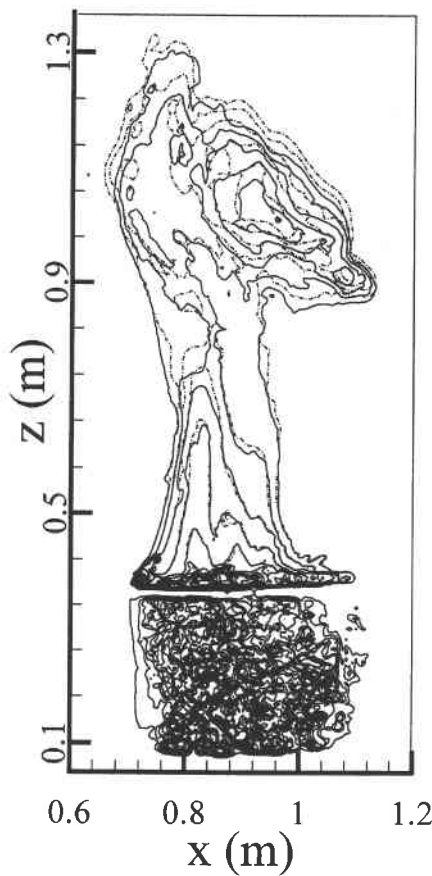


Figure 4. Movement of successive images of temperature contours measured from thermal IR camera for chamise fire plume with a time difference 0.0167 s or sampling rate 60 Hz. The solid line corresponds to the first image and the dashed line to the later one.

experiment using chamise as fuel. Two temperature contours are overlapped and the later one is illustrated as a dashed line. The time difference is 0.0167 s. Because burning occurs in the fuel bed, a high temperature and dense contours can be found in the container. Comparing with the fire plume of alcohol, the flame length of chamise is higher. As seen in Figure 4, over a short time period, a minor upward movement of the temperature field can be observed.

Figure 5 illustrates the velocity field estimated by the TPIV algorithm. Because the domain of the IR image of chamise is a little bigger, a

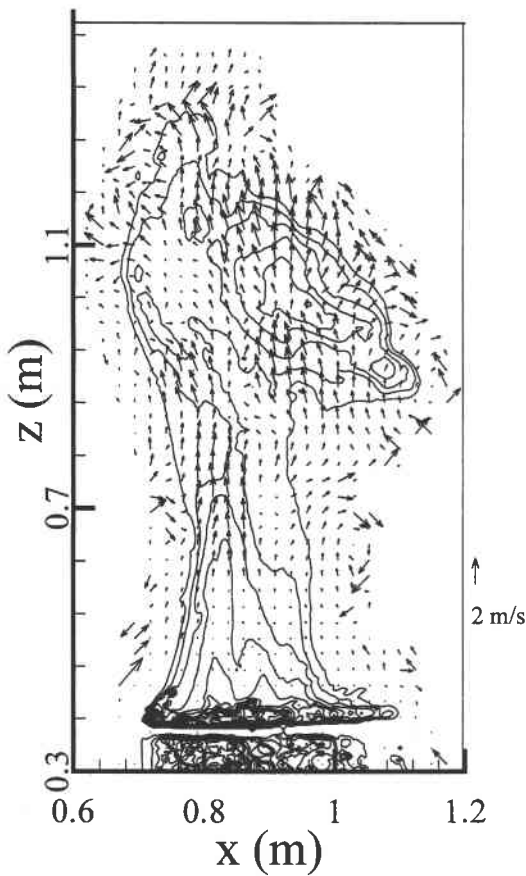


Figure 5. Velocity vector field estimated by the TPIV algorithm using temperature images measured from thermal IR camera for chamise fire plume. Sampling rate is 60 Hz. The patch size is 13×13 . Temperature contours are illustrated to show the flame shape.

larger patch size of 13×13 was used. The estimated velocity field of chamise fire plume looks similar to that of alcohol fire (see Figures 5 and 3). There is an accelerating central core and rotation in the fire plume. The maximum vertical speed is about 2.2 m/s. Because there are no accurate measures of instantaneous velocity fields at the present time, the estimated velocities obtained from IR images are not validated. This will constitute part of our future work. Based on observations during the experiment, the estimated velocity field using the TPIV algorithm appears reasonable. In the next section, we provide partial validation of the TPIV algorithm by comparing the estimates with predicted velocities from the FDS code.

Estimated Velocity from Computed Temperature Images

Figure 6 illustrates two successive temperature contours computed from the FDS code for the pool fire using the assumed heat release rate. A vertical x - z plane along the center of the computational domain is illustrated. In order to clearly show the movement of temperature fields with

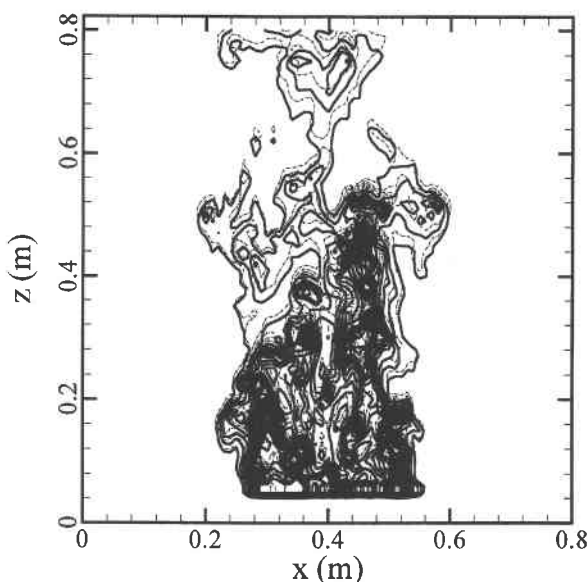


Figure 6. Movement of successive images of two-dimensional temperature contours (K) calculated from the FDS code for the pool fire with a time difference 0.00687 s or sampling rate 145 Hz. The solid line corresponds to the first image and the dashed line to the later one.

time, two temperature contours are overlapped and the later one is illustrated as a dashed line. The time difference is 0.00687 s corresponding to a sampling rate of 145 Hz. Over this short time period, a minor upward movement of the temperature fields can be observed; however, the shape of the temperature images does not change significantly. This suggests that the assumption that the signal from a thermal particle is conserved over a short time is valid.

Figures 7a and 7b show a comparison of the velocity vectors computed from the FDS code and that estimated from the TPIV algorithm, overlaying the background temperature field. A patch size of 9×9 grid points is used at an image sampling rate of 145 Hz. Because the velocity field estimated by the TPIV algorithm is taken from the average of three images, the estimated velocity field appears smoother than the instantaneous velocity field calculated by the FDS code. Overall, both velocity fields compare well in the fire-plume region. There are upward velocity vectors in the core region and minor rotating vortices at the edge of the fire plume.

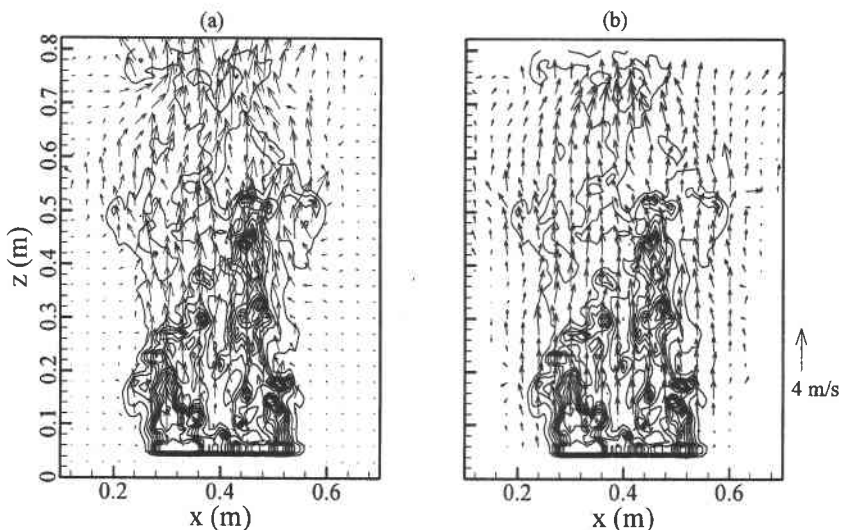


Figure 7. Comparison of velocity vector field (a) computed from FDS code and (b) estimated by the TPIV algorithm using temperature images obtained from FDS code. Sampling rate is 145 Hz. The patch size is 9×9 . Temperature contours are illustrated to show the flame shape.

It is noted that the TPIV algorithm is different from PIV. For PIV, the instantaneous velocity field is obtained by recording the position of seed particles at successive time images. In the TPIV method, the seed particles are not real particles, but “hot” pixels resolved in digital IR images that are named as thermal particles. Some problems such as seeding and whether the seed follows the flow will not appear in the TPIV algorithm. As discussed earlier, the patch size of thermal particles depends on the image sampling rate. For the TPIV algorithm, one basic condition is that a thermal particle should exist in the domain corresponding to two successive images. If the fluid flow is too fast or the time difference of two images is too large, the thermal particle in frame 1 will not appear in frame 2 because the particle may move out of the domain defined by a patch of grid points. Of course the patch size can be increased; however, a large patch size can make the velocity averaged over a large physical space smooth the turbulent velocity field. For an image sampling rate f , maximum fluid velocity $U_{\max}$ and grid size δ_x , a possible patch size ($N \times N$) may be approximated as

$$N \geq \frac{2U_{\max}}{\delta_x f} + 1 \quad (24)$$

where the thermal particle is located in the center of a patch of $N \times N$ grid points; then the possible movement of the thermal particle is limited to half of $(N - 1)$ grid distance. For the present numerical calculation, the approximate maximum velocity is $U_{\max} = 6.0$ m/s and $\delta_x = 0.01$ m. For sampling rate $f = 145$ Hz, the minimum patch size is about $N = 9$. If the rate is increased to $f = 245$ Hz, the required patch size is about $N = 5$. Following this discussion, Figure 8 illustrates the effect of different patch size on the vertical velocity profile estimated by the TPIV algorithm. Five patch sizes of 13, 11, 9, 7, and 5 are utilized to estimate the velocity at a fixed image sampling rate of 245 Hz. At a height $z = 0.55$ m, Figure 8 shows that velocity profiles with large patch size are smoother than those with small patch size. This is because of the summation that is taken in forming the function Λ is minimized. A patch of grid points is used to estimate the displacement Δx and Δz . A large patch size means the velocity is averaged over a large physical space which leads to the smoothing or filtering of the velocity field.

In a region with uniform temperature, the function Λ might also be minimized even if Δx and Δz are inaccurate since the new location

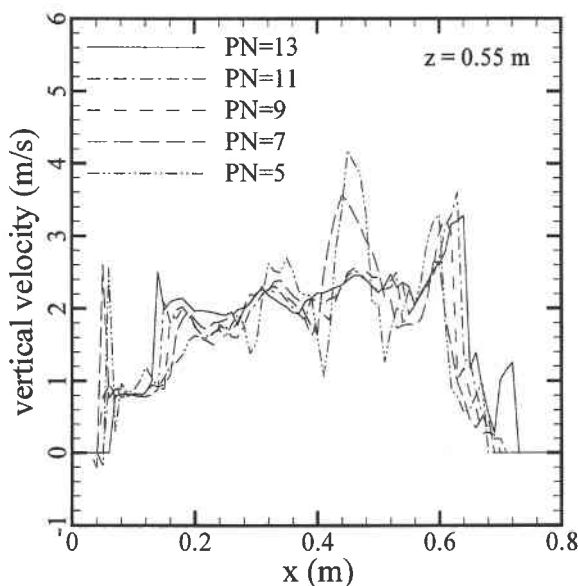


Figure 8. Comparison of vertical velocity profiles estimated by the TPIV algorithm for five patch sizes at a fixed image sampling rate of 245 Hz.

estimated by these incorrect Δx and Δz would possess the same temperature as that at the previous position. This could easily happen at the edge of a fire plume where temperature is relatively uniform because of the entrainment of cold air. Following the discussion on patch size, it means that spatial and temporal resolutions play an important role in the TPIV algorithm. The temporal resolution depends on the image sampling rate. The time difference between two images has to be sufficiently small so that the image does not displace too much to estimate the correct Δx and Δz . Accordingly, we would obtain sufficiently small Δx and Δz to reasonably truncate higher order terms in the Taylor series approximation of temperature function as described in Eq. (2).

Following the preceding discussion, Figures 9 to 11 present a comparison of estimated velocity profiles with simulated data from FDS code at three vertical heights. Two sampling rates of 145 and 245 Hz are used to illustrate the effect of image sampling rate on the estimated velocity. The patch size is 9×9 . As seen in Figures 9 to 11, at height $z = 0.65$ m, the estimated velocity profiles agree well with that from FDS code. At a lower section at $z = 0.40$ m, however, high turbulent velocities are not

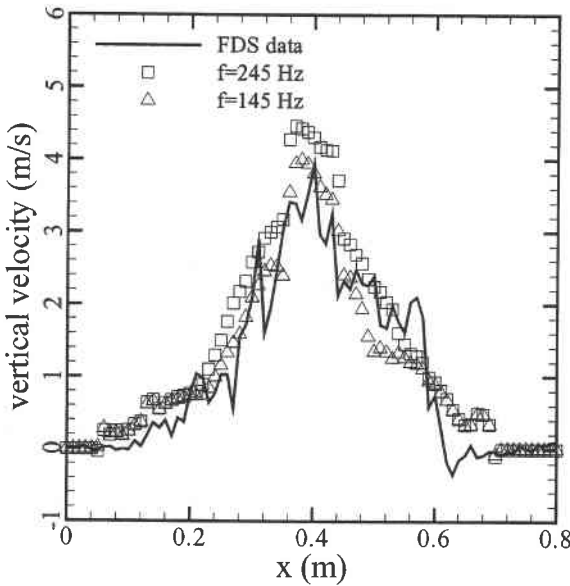


Figure 9. Comparison of vertical velocities (at $z = 0.65$ m) computed by the FDS code and estimated by the TPIV algorithm with two different image sampling rates.

detected by the TPIV algorithm. The estimated velocity profiles are smoothed. This can be explained by observing the movement of temperature contours shown in Figure 6. The lower section corresponds to the core region of the fire plume. In this region, there are strong chemical reaction processes between fuel and air and radioactive heat release due to high temperature. Here the movement and change of temperature contours not only depend on the fluid flow but also on combustion processes and heat release. However, at the upper region, the temperature is lower and the fuel combustion is almost complete. The temperature contours move upward mainly with the fluid flow. As shown in Figure 6, the shape of temperature contours at the upper region has no significant change and the movement with time is clear. This allows the TPIV algorithm to detect displacements Δx and Δz with better accuracy.

The effect of image sampling rate on the estimated velocity is evident. The velocity estimated by high rate was larger than that by low rate. In general, the accuracy of the TPIV algorithm with high rate is better. This result follows the discussion on temporal resolution. Using a high rate, the time difference between two images is small and the images do not displace

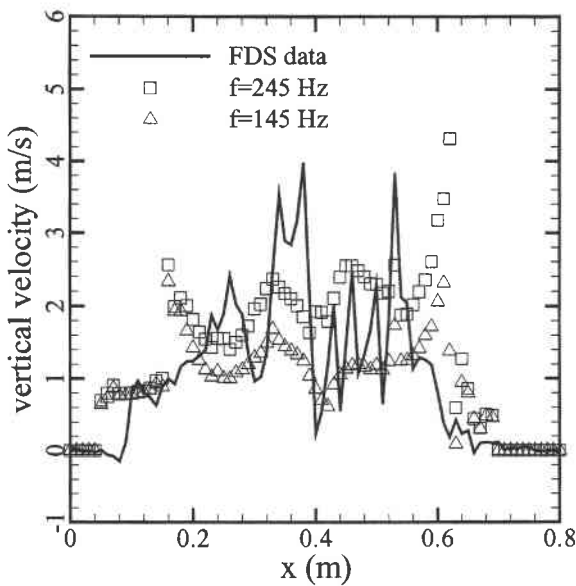


Figure 10. Comparison of vertical velocities (at $z = 0.55$ m) computed by the FDS code and estimated by the TPIV algorithm with two different image sampling rates.

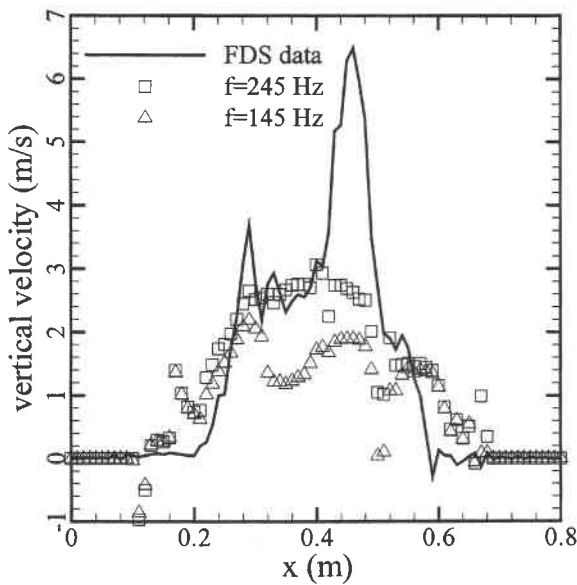


Figure 11. Comparison of vertical velocities (at $z = 0.4$ m) computed by the FDS code and estimated by the TPIV algorithm with two different image sampling rates.

too much. A small Δx and Δz also leads to an acceptable Taylor series approximation for temperature function described in Eq. (2). Of course, in engineering applications, the high sampling rate is limited by the thermal IR camera. An acceptable sampling rate might also depend on the domain size of the thermal images and the speed of the fluid flow. In the experiment of a wildfire examined by Clark et al. (1999), the domain size of the IR thermal image is 20×20 m and the time step used is from 0.03 to 66 s. The results obtained by gradient-based algorithm were reasonable, showing two rising towers of hot, rotating air that were consistent with vorticity at the fire front undergoing enhanced vortex tilting.

CONCLUSION

The use of thermal IR imagery as a tool to estimate flame velocities in wildland fires was investigated. A TPIV algorithm of non-intrusively measuring flame gas velocities through IR image was developed. By tracing thermal particles in successive digital IR images, the results show that the TPIV algorithm is capable of deriving fire flow on a small range of spatial and temporal scales associated with fire spread. By comparing with instantaneous velocities calculated by the FDS code, it is shown that the image sampling rate and patch size influence the accuracy of TPIV algorithm. Within the limits of thermal IR camera, a larger sampling rate is required. Overall, the velocities estimated by the TPIV algorithm appear reasonable, although the velocity fields obtained from IR images of alcohol and chamise fire plumes have not been validated. This is part of our future work to measure the velocity field. For wildfire research, this method of nonintrusively measuring fluid flow will be useful for us to describe the small temporal and spatial scales involved in fire vortices that help determine fire spread.

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