

# **A Novel Technique of Computational Vision Based Flame Detection Using Optical Flow Estimation**

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**ABSTRACT:** Detecting the breakout or flow of fire is essential for preventing material damage and human casualties. It is a serious problem in situation such as congested automobile traffic, naval vessels and heavy industry. By observing this problem, Classical optical flow method is used. Optical flow estimation computes correspondence between pixels in the current and previous frame of an image sequence. Classical optical flow estimation is a combination of linear and non linear scale-space varies smoothly in image. It mainly detect the brightness constancy fire region and satisfy the intensity assumption. But this method do not model the characteristics of fire motion in large open spaces such as hangers, ships, or in forest. To overcome the insufficiencies of classical optical flow two methods are proposed. First is Optical Mass Transport, this method is used for identifying rapid and smoothness regularization of fire. Second is Non Smooth Data, it is used in unfavourable lightning condition. By these method the flow magnitudes and directions are calculated from the flow fields to know the fire and non fire motion. These features are tested in a large database to demonstrate their practical usefulness.

**KEYWORDS:** Fire detection, optical flow, optimal mass transport, video analytics.

## **I. INTRODUCTION**

DETECTING the break-out of a fire rapidly is vital for prevention of material damage and human casualties. This is a particularly serious problem in situations of congested automobile traffic, naval vessels, and heavy industry. Traditional point-sensors detect heat or smoke particles and are quite successful for indoor fire detection. However, they cannot be applied in large open spaces, such as hangars, ships, or in forests. This paper presents a video-detection approach geared toward these scenarios where point-sensors may fail. In addition to covering a wide viewing range, video cameras capture data from which additional information can be extracted; for example, the precise location, extent, and rate of growth. Surveillance cameras have recently become pervasive, installed by governments and businesses for applications like license-plate recognition and robbery deterrence. Reliable vision-based fire detection can feasibly take advantage of the existing infrastructure and significantly contribute to public safety with little additional cost. Vision-based detection is composed of the following three steps. Preprocessing (1) is necessary to compensate for known sources of variability, e.g., camera hardware and illumination. Feature extraction (2) is designed for the detection of a specific target; a computation maps raw data to a canonical set of parameters to characterize the target. Classification algorithms (3) use the computed features as input and make decision outputs regarding the target's presence. Supervised machine-learning-based classification algorithms such as neural networks (NN) are systematically trained on a data-set of features and ground-truth. While aspects of preprocessing (1) and classification (3) are considered, the paper focuses on feature extraction (2). Motivated by physical properties of fire, a set of novel optical flow features are designed for vision-based fire detection.

## II. LITERATURE REVIEW

Computer vision concepts are often inspired by human vision. A comprehensive and elegant description of the human perception of fire was presented by the 16th century French poet Du Bartas [1]: “Bright-flaming, heat-full fire, the source of motion.” Whereas Du Bartas missed the characteristic reddish color that almost any vision-based detection algorithm builds upon, e.g., [2], his quote covers most of the other features employed by previous methods. High brightness or luminance causes image pixels to saturate—one feature utilized in [3]–[5]. The instantaneous flame-like texture or spatial pattern are used in [4], [6], [7]. Features related to the flame’s shape and change of shape are found in [3], [6], [7]. Also, the flickering, typical of fire, presents a popular feature [3], [4], which has also been analyzed in the wavelet domain [8], [9]. This paper is restricted to studying images in the visible spectrum and emitted heat or infrared light is not considered, but it is used in a number of approaches where infrared sensors are available [10]. Lastly, fire motion offers a whole suite of possible features. The authors of [11] consider the temporal variation of pixel intensity for fixed pixel locations. More recently, [12] develops a more comprehensive statistical approach by computing covariances of image quantities on small blocks, thus making use of spatial and temporal patterns. These statistics are applied directly to the image data and these methods are therefore comparably efficient. Optical flow estimators, on the other hand, transform the image sequence into estimated motion fields, allowing for a more insightful extraction of features. Classical optical flow algorithms are analyzed in [13] for the recognition of various dynamic textures.

## III. OPTICAL FLOW ESTIMATION

The paper’s focus is put on the feature extraction block, where two optical flow fields (OMT and NSD) are computed in parallel from which the 4D feature vector is built.

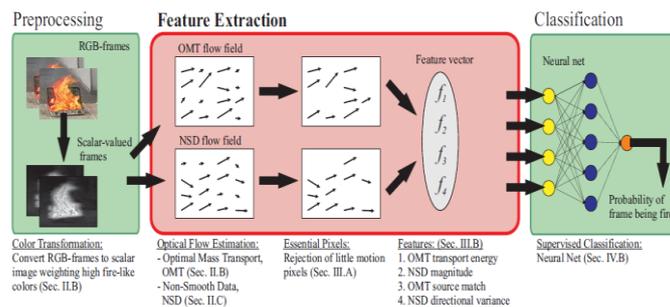


Fig. 1. Architecture diagram for flame detection

### A. Classical Optical Flow

Optical flow estimation computes correspondence between pixels in the current and the previous frame of an image sequence. Central to most approaches in establishing this correspondence is the assumption of intensity constancy: moving objects preserve their intensity values from frame to frame. This assumption leads to the optical flow constraint

$$\frac{d}{dt} I = I_x u + I_y v + I_t = 0$$

where  $I(x, y, t)$  is a sequence of intensity images with spatial coordinates  $(x, y) \in \_$  and time variable  $t \in [0, T]$  (subscripts denote partial derivatives).

### B. Optimal Mass Transport (OMT) Optical Flow

Classical optical flow models based on brightness constancy,  $d/dt I = 0$ , are inadequate to model the appearance of fire for two reasons. First, fire does not satisfy the intensity constancy assumption Eq. (1), since rapid (both spatially and temporally) change of intensity occurs in the burning process due to fast pressure and heat dynamics. Second, smoothness regularization may be counter-productive to the estimation of fire motion, which is expected to have a

turbulent, i.e., non-smooth, motion field. For these reasons, an optical flow estimation modeling fire as a dynamic texture, the optimal mass transport (OMT) optical flow, was introduced in [24]. A review of the OMT optical flow is given next.

**1) Derivation:** The optical flow problem is posed as a generalized mass—representing image intensity  $I$ —transport problem, where the data term enforces mass conservation. The conservation law is written as

$$I_t + \nabla \cdot (\vec{u}I) = 0$$

where  $\mathbf{u} = (u, v)^T$ . With intensity  $I$  replaced by mass density.

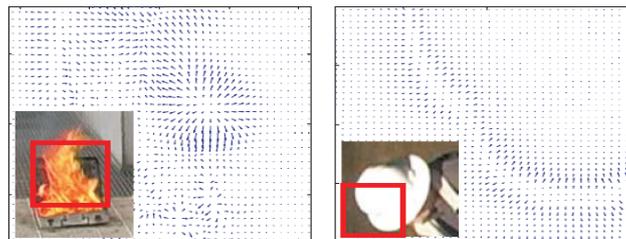


Fig. 2. OMT flow fields: fire with dynamic texture (left) and a white hat (right) moving up/right. The red box indicates the area for which the flow field is shown.

**2) Flame Color as Generalized Mass:**

In the original OMT optical flow [24] formulation, the generalized mass is the pixel intensity  $I$ . This choice is based on the assumption that high gas density translates to high intensity in the image.

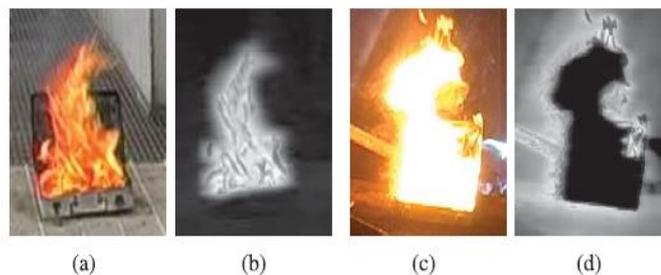


Fig. 3. Two examples for the generalized mass transformation

(a) and (c): Original images. (b) and (d): Respective generalized mass (black - 0, white - 1). Fire texture is preserved, saturated regions are assigned as low mass.

However, there are other phenomena that map to high intensities also, such as the sky on a sunny day or a white wall. In order to improve the chance of good segmentation between foreground and background, this section introduces a new model for the generalized mass based on flame color.

**C. Non-Smooth Data (NSD) Optical Flow**

Under unfavorable lighting conditions, especially in closed spaces, fire blobs are likely saturated, thus violating OMT’s assumption that dynamic texture is present in fire. Nevertheless, these blobs have boundary motion, which may be characterized by another type of optical flow estimation. A novel optical flow energy functional called Non-Smooth Data optical flow (NSD) and tailored to saturated fire blobs is proposed as

$$\min_{\vec{u}} \frac{1}{2} \int_{\Omega} \int_0^1 (I_t + \nabla I \cdot \vec{u})^2 + \alpha \|\vec{u}\|_2^2 dt dx dy.$$

The choice of the data term being the optical flow constraint is justified because pixel saturation trivially implies intensity constancy. Also, the NSD is explicitly chosen to be non-smooth since saturated fire blobs are expected to have non-smooth boundary motion.

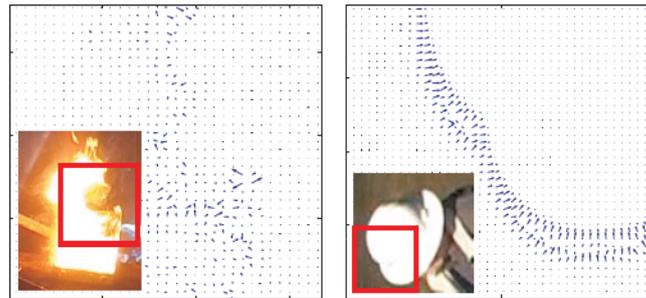


Fig. 4. NSD flow fields: saturated fire (left) and a white hat (right) moving up/right. The red box indicates the area for which the flow field is shown.

The Fig. 4 shows NSD flow fields computed for a saturated fire and a rigidly moving hat. Fire motion on the boundary is non-smooth in contrast to the hat's motion—a result from the data-driven formulation of the NSD.

#### IV. OPTICAL FLOW FEATURES

A naive approach to vision-based detection is to use a supervised machine learning algorithm trained directly on intensity values in the image. This approach will undoubtedly underperform because the classification complexity increases exponentially with the dimensionality of the problem, which in this case is equal to the number of pixels. Further, the computational cost and the amount of training data required become prohibitively large. Instead, feature extraction is employed by incorporating prior information (known physical properties of the problem or human intuition) for the purpose of reducing the problem dimensionality. The optical flow computations in Section II do not reduce dimensionality, as the two  $M \times N$  images determine the values of the  $M \cdot N$ , 2D, optical flow vectors. This transformation is an intermediate step that provides a data set from which motion features can be extracted more intuitively than would be possible from the original image. To do so, we pursue a region-based as opposed to a pixel-based approach. Whereas the pixel-wise approach classifies each pixel, the region-wise approach aims to classify a region as a whole by analyzing the set of all pixel values (in this case flow vectors) in that region.

In the following section, the proposed feature extraction is defined and motivated.

##### A. Pre-Selection of Essential Pixels

Static or almost static image regions should be excluded from consideration because our aim is to characterize the type of motion an object is undergoing and they interfere with the motion statistics. For example, the average flow magnitude of a moving object should not depend on the size of the static background, which would be the case if the average was computed over the entire image instead of just the moving region. The set of essential pixels, which are pixels in motion, will therefore be defined as follows.

##### B. Feature Extraction

In [13] a list of optical flow features is introduced, which is complete in that it considers all possible first-order distortions of a pixel. Those distortions are then averaged within a spatiotemporal block to yield the probability of a characteristic direction or of a characteristic magnitude. Reference [13] also mentions that the highest discriminating power comes from the characteristic direction and magnitude of the flow vector itself, not considering distortions. This observation matches our experience from early prototyping where flow derivatives seemed to have very little discriminating power and were thus removed from further consideration.

1) **OMT Transport Energy:** This feature measures the mean OMT transport energy per pixel in a subregion

$$f_1 = \text{Mean}_{\Omega_e} \left( \frac{I}{2} \|\bar{\mathbf{u}}_{\text{OMT}}\|_2^2 \right)$$

After the color transformation, fire and other moving objects in the fire-colored spectrum, are expected to produce high values for this feature.

2) **NSD Flow Magnitude:** Similarly, the mean of the regularization term of the NSD optical flow energy constitutes the second feature

$$f_2 = \text{Mean}_{\Omega_e} \left( \frac{1}{2} \|\bar{\mathbf{u}}_{\text{NSD}}\|_2^2 \right)$$

The first two features,  $f_1, f_2$ , will have high values for moving, fire-colored objects. The last two features distinguish turbulent fire motion from rigid motion by comparing flow directionality.

3) **OMT Sink/Source Matching:** It is known [30] that solutions to OMT problems are curl-free mappings. For the turbulent motion of fire, this property tends to create flow fields with vector sinks and sources. For rigid motion, the flow field tends to be comprised of parallel vectors indicating rigid translation of mass. The third feature is designed to quantify how well an ideal source flow template matches the computed OMT flow field. The template is defined as

$$\bar{\mathbf{u}}_T(x, y) = \begin{pmatrix} u_T(x, y) \\ v_T(x, y) \end{pmatrix} = \exp \left( -\sqrt{x^2 + y^2} \right) \begin{pmatrix} x \\ y \end{pmatrix}$$

4) **NSD Directional Variance:** The final feature distinguishes the boundary motion of saturated fire blobs from rigidly moving objects by quantifying the variance of flow directions at moving pixels. A high variance suggests uncorrelated motion in many different directions, whereas a low variance characterizes nearly uni-directional motion.

## V. DETECTION ALGORITHM

This section touches on two more topics required for an end-to-end detection system. The candidate regions, i.e., suspicious subregions of the image, can be created automatically and why this step is important. Then, how a candidate region is classified as fire or non-fire based on its feature vector,  $F$ .

### A. Providing Candidate Regions

Computing optical flow and extracting features from an entire frame is unfavorable for two reasons. First, computation time increases as the domain  $\Omega$  grows, and more importantly, the classification fails for scenes with more than one source of motion (e.g., a fire in the corner and a person walking in the center) since the motion statistics of the regions will be averaged and become no longer discriminatory. Therefore, it is essential for the proposed method that a segmentation of different sources of motion be provided, which the detection algorithm then classifies individually.

### B. Region Classification via Neural Network

The simplest way of classifying a candidate region based on its feature vector  $F = (f_1, f_2, f_3, f_4)^T$  is to threshold each of the features  $f_i$  based on heuristically determined cutoff values and make a decision by majority voting. However, better results can be achieved by learning the classification boundary with a machine learning approach such as neural networks. Training the neural network (NN) means performing a non-linear regression in the feature space to best separate the labeled training data into classes.

## VI. TESTS ON VIDEO DATABASE

The algorithm is tested on a database provided by United Technologies Research Center (UTRC), Connecticut, USA. The database features various scenarios including indoor/outdoor, far/close distance, different types of flames (wood, gas, etc.), changing lighting conditions, partial occlusions, etc.



Fig. 5. Examples of detected fire scenes with the resulting probabilities.

The videos have a frame rate of 30 frames/second and spatial dimension of 240 by 360 pixels. From each of the 263 scenarios (containing 169 fire and 94 non-fire sequences), 10 consecutive frames are labeled as ground truth providing a test database of 2630 frames. Note that the non-fire scenarios are chosen to be probable false positives, namely moving and/or fire-colored objects such as cars, people, red leaves, lights and general background clutter. A neural network was trained on frames from 20 of those videos not used in the test database. The test result shows that fire is reliably detected using optical flow features only: the false positive rate (fire is detected when no fire is present) is  $fp = 3.19\%$  and the false negative rate (no fire detected where there is a fire) is  $fn = 3.55\%$ . These false detection rates are competitive with recently published, full-fledged fire detection systems, e.g. [2]:  $fp = 31.5\%$ ,  $fn = 1.0\%$ , [3]:  $fp = 0.68\%$ ,  $fn = 0.028\%$ , [4]:  $fp = 0.30\%$ ,  $fn = 12.36\%$ , [12] (average among test videos):  $fp = 3.34\%$ ,  $fn = 21.50\%$ . Since this paper explores the discriminatory power of optical flow features only rather than building a complete fire detector, we report the false detection rates as a feasibility check that the proposed features work on a large set of data.

## VI. CONCLUSION

The very interesting dynamics of flames have motivated the use of motion estimators to distinguish fire from other types of motion. Two novel optical flow estimators, OMT and NSD, have been presented that overcome insufficiencies of classical optical flow models when applied to fire content. The obtained motion fields provide useful space on which to define motion features. These features reliably detect fire and reject non-fire motion, as demonstrated on a large dataset of real videos. Few false detections are observed in the presence of significant noise, partial occlusions, and rapid angle change. In an experiment using fire simulations, the discriminatory power of the selected features is demonstrated to separate fire motion from rigid motion. The controlled nature of this experiment allows for the quantitative evaluation of parameter changes. Key results are the need for a minimum spatial resolution, robustness to changes in the frame rate, and maximum allowable bounds on the additive noise level. Future work includes the development of optical flow estimators with improved robustness to noise that take into account more than two frames at a time.

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