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Pattern Classification Techniques for Flame Detection in Videos Using Optical Flow Estimation

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ABSTRACT

Vision based fire detection is potentially a useful technique. Vision-based detection is composed of the following three steps. Preprocessing is necessary to compensate for known sources of variability. Feature extraction is designed for the detection of a specific target. Classification algorithms 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. Since classical optical flow methods do not model the characteristics of fire motion two optical flow methods are specifically designed for the fire detection task: optimal mass transport models fire with dynamic texture, while a data-driven optical flow scheme models saturated flames. Then, characteristic features related to the flow magnitudes and directions are computed from the flow fields to discriminate between fire and non-fire motion.

Keywords: Fire detection, optical flow, optimal mass transport, video analysis.

I. INTRODUCTION

Fire has unique visual signatures. Color, geometry, and motion of fire region are all essential for recognition. A region that corresponds to fire can be captured in terms of spectral characteristics of the pixels in the region, and the spatial structure defined by their spectral variation within the region [1]. The shape of a fire region usually keeps changing and exhibits a stochastic motion, which depends on surrounding environmental factors such as the type of burning materials and air flow. The pixels in a fire region have characteristic color spectra and the pixels with different spectra have characteristic relative locations. In color images, fire regions are bright white color in the core, and yellow, orange and red away from the core.

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II. OBJECTIVE

- To develop a model which automatically detect the flames in videos.
- To extract a features using Optical Mass Transport (OMT) and Non Smooth Data (NSD) algorithms.
- To detect the flame region in the video using Backpropagation Neural Network (BPNN).

III. BLOCK DIAGRAM OF THE PROPOSED WORK

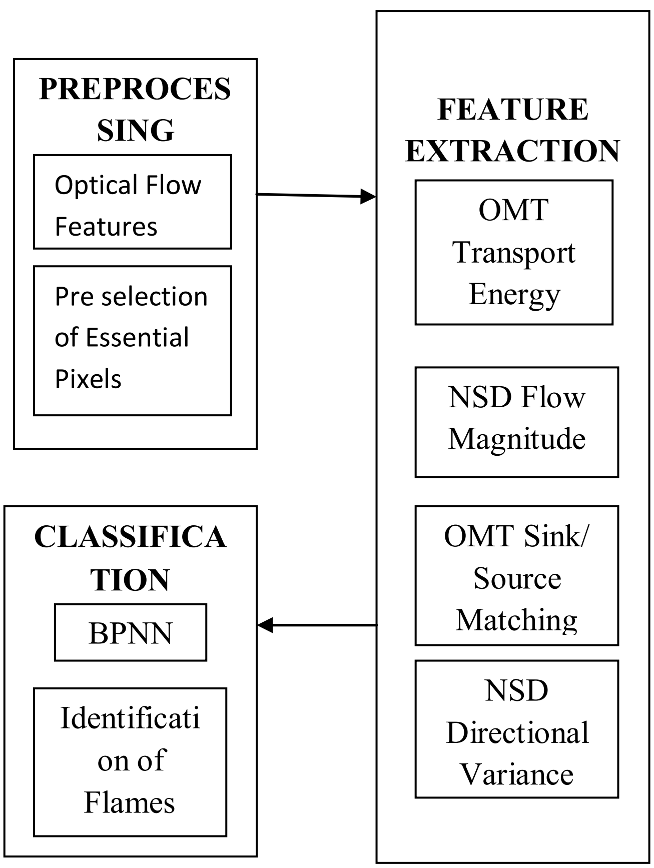

Fig.1 Block diagram

A. PREPROCESSING

Figure 2 shows the overall block diagram of the proposed work. Color vision can be processed using RGB color space or HSV color space [2]. RGB color space describes colors in terms of the amount of red, green, and blue present. HSV color space describes colors in terms of the Hue, Saturation, and Value.

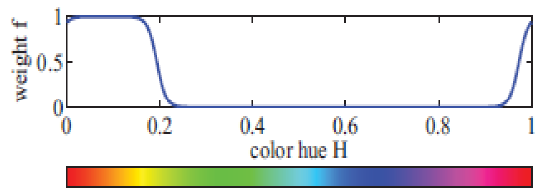

Fig. 2 Hue Term

$$I = f(\min\{|H_c - H|, 1 - |H_c - H|\}) \cdot S \cdot V \quad (1)$$

The transformation in equation 1 will weight highly only the periphery of saturated fire regions where camera-saturation tends to occur less. This property becomes visible in Figure 3 (c) and (d), where the core of the fire center is saturated. The fire texture in Figure 3 (a), on the other hand, is preserved in the generalized mass Figure 3 (b).

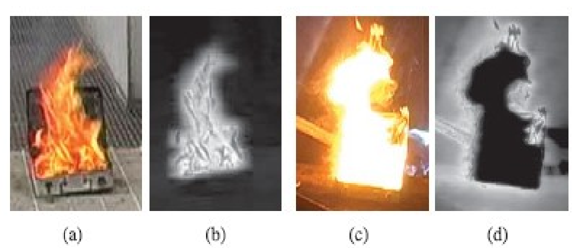

Figure 3 (a) and (c): Original images (b) and (d): Respective generalized mass

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Figure 4 (a) and (b) shows two examples of OMT flow fields computed from the generalized mass images [4]. It illustrates OMT's ability to capture dynamic texture for the fire image and discriminate between the rigid object's flow field, which appears much more structured.

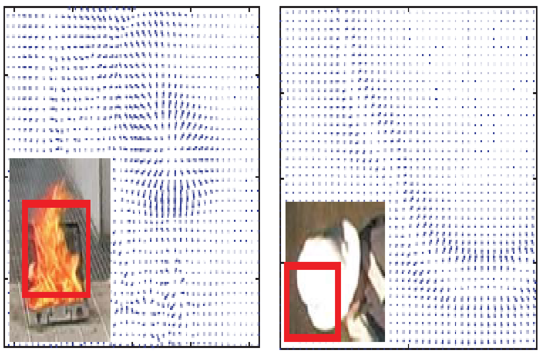

Figure 4 (a) and (b) OMT Flow Field

B. OPTICAL FLOW FEATURES

The optical flow computations do not reduce dimensionality, as the two M×N images determine the values of the M・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 [6]. 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.

C. 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 [3]. 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.

D. FEATURE EXTRACTION

In a list of optical flow features is introduced, which is complete in that it considers all possible first-order distortions of a pixel [5]. Those distortions are then averaged within a spatiotemporal block to yield the probability of a characteristic direction or of a characteristic magnitude. In particular, our magnitude features f_1 and f_2 measure mean magnitude as opposed to relative homogeneity of the magnitudes [7]. The other two features f_3 and f_4 then analyze motion directionality. Thus, given an image region Ω and the optical flow fields $\vec{u}_{OMT}$

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and $\vec{u}_{NSD}$ in that region, the features are chosen as follows.

a. OMT Transport Energy: This feature measures the mean OMT transport energy per pixel in a sub region.

$$f_1 = \underset{\Omega_e}{\mathrm{Mean}}\left(\frac{I}{2}\left\|\vec{u}_{OMT}\right\|_2^2\right) \tag{2}$$

Where I is the intensity, $\vec{u}_{OMT}$ is the optical flow field represented in the two dimensional space in equation 2.2, it shows the direction of the pixels.

b. NSD Flow Magnitude: Similarly, the mean of the regularization term of the NSD optical flow energy constitutes the second feature.

$$f_2 = \underset{\Omega_e}{\mathrm{Mean}}\left(\frac{I}{2}\left\|\vec{u}_{NSD}\right\|_2^2\right) \tag{3}$$

Where $\vec{u}_{NSD}$ is the optical flow field represented in the two dimensional space in equation 2.3, it shows the magnitude between the pixels [7]. 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.

c. OMT Sink/Source Matching: It is known that solutions to OMT problems are curl-free mappings.

$$f_3 = \underset{\Omega}{\mathrm{Max}}\left|\left(u_T * \frac{u_{OMT}}{\left\|\vec{u}_{OMT}\right\|_2}\right) + \left(v_T * \frac{v_{OMT}}{\left\|\vec{u}_{OMT}\right\|_2}\right)\right| \tag{4}$$

where* denotes convolution, u, v are flow 3.4 vectors, u_T, v_T are flow vectors templates and x, y are spatial coordinates.

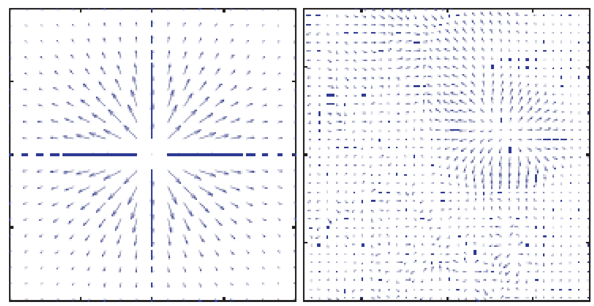

Figure 5 (a) Ideal source flow template and (b) OMT flow field for the fire image

d. 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.

$$f_4 = \mathrm{Var}\{S_i,\ i = 0, \ldots\ldots, n-1\} \tag{5}$$

Where

$$s_i = \frac{\int_0^{\infty}\int_{2\pi i/n}^{2\pi(i+1)/n} h(r,\phi)\,d\phi\,dr}{\int_0^{\infty}\int_0^{2\pi} h(r,\phi)\,d\phi\,dr} \tag{6}$$

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E. CLASSIFICATION

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.

a. NEURAL NETWORKS

Neural Networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns [9] and detect trends that are too complex to be noticed by either humans
or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze.

b. BACKPROPAGATION NEURAL NETWORKS

The backpropagation neural network (BPNN) was developed by Rumelhart as a solution to the problem of training multi-layer perceptrons. The fundamental advances represented by the BPNN were the inclusion of a differentiable transfer function at each node of the network and the use of error back-propagation to modify the internal network weights after each training epoch. The backpropagation neural networks used in this work all have three layers of neurons, or nodes (input, hidden, and output).

c. PHASES OF BPNN

The Backpropagation learning algorithm can be divided into two phases: Propagation and Weight update.

For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Subtract a ratio (percentage) of the gradient from the weight.

IV. IMPLEMENTATION

A. TRAINING AND TESTING FOR CLASSIFICATION OF FLAMES

The input video samples are trained by applying the Optical Mass Transport and Non Smooth Data. After applying the OMT and NSD the features are extracted. The extracted features are given to the neural network classifier and the results are saved. Then the features are extracted using OMT and NSD from the test video and the extracted features are given to neural network classifier. The results are compared

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with the trained samples result and it shows the result of flame detection.

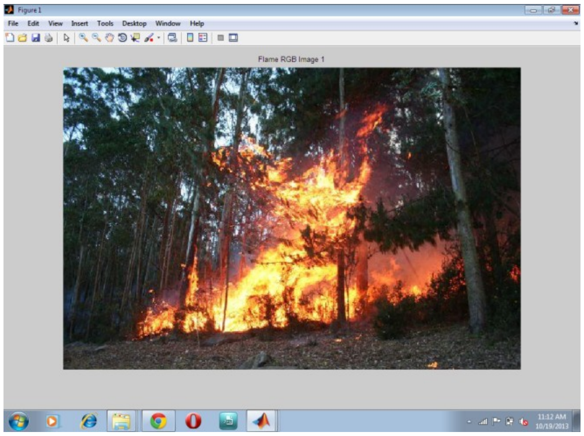

Figure 6 Original Image

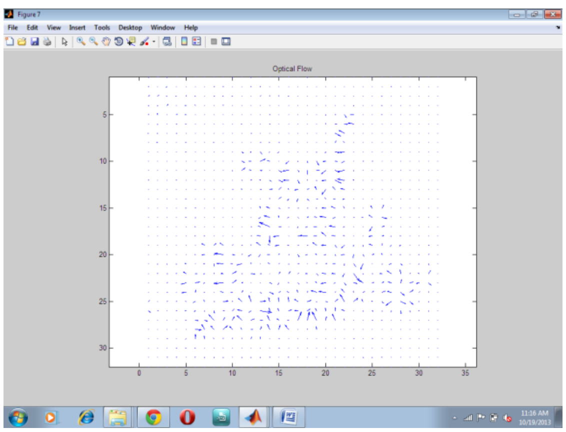

Figure 7 OMT Flow Field

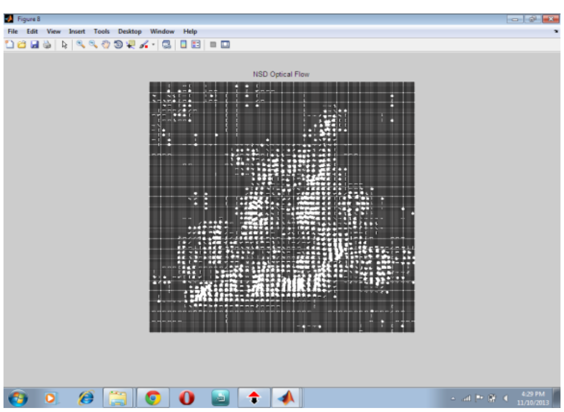

Figure 8 NSD Optical Flow Field

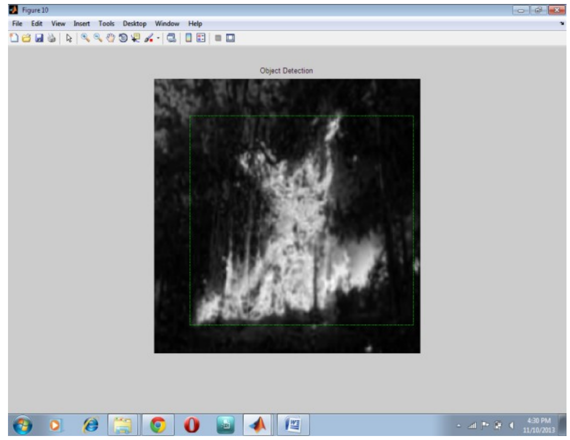

Figure 9 Object Detection

V. CONCLUSION AND FUTURE ENHANCEMENTS

A. CONCLUSION

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.

B. FUTURE ENHANCEMENTS

Little false detections are observed in the presence of significant noise, partial occlusions, and rapid angle change. 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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