

Thermal Abnormality Detection from Videos Based on Refractive Flow

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Abstract. In this paper, we attempt to detect thermal abnormality in a scene from image sequences. The abnormal regions in the images are visualized by detecting refractive flows caused by heat sources. To avoid being affected by intrinsic fluid flows in a scene, the flow field under a normal condition is used as a priori information. The possibility of a point being abnormal is then determined by Bayesian principle. The intention of this method is an implementation of fire prevention by raising an alarm before the emergence of flame or smoke.

1 Introduction

Fire prevention is essential for warehouses, laboratories, etc. Current physical sensors, such as smoke detectors, require a certain concentration of smoke to trigger alarms. Further approaches introduce thermal cameras to detect infrared heat[1], but thermal energy can be reflected off by shiny surfaces like glass and polished metal, thus thermal cameras cannot see through glass. In computer vision, flames and smoke are detected from videos using color or statistical features[2,3]. We intend to implement fire prevention using security cameras and raising an alarm once a local temperature abnormality occurs.

A rise in temperature would cause a change in the local air refractive index. When a light is passing through the refractive air, it would ultimately cause certain distortions in images. These distortions are cues to locate refractive flows in images, and detect thermal abnormality regions. The work of Xue et al. provides an effective approach of detecting refractive flows in images using wiggle feature[4]. However, this method is not designed for a particular kind of flow. Since refractive flows near the receiver aperture have a greater impact on imaging, the target signals are submerged in other fluid flows intrinsic to the scene, such as those caused by air conditioners. Moreover, the experiments in [4] utilizes high-frame cameras(up to 1000fps). We hope that the specific fluid flows caused by thermal abnormality can be detected by a camera for practical use.

In this paper, fluid flow field in normal cases is viewed as a background, and fluid flows caused by thermal abnormality are viewed as foregrounds. Then the problem is converted to the detection of foreground fluid flows against backgrounds. Motions of fluid flow fluctuate randomly everywhere in the image. However, for a single point, the range of fluctuation depends on the region it belongs to. For example, the fluctuation range of a point on a window may be greater than that on a texture-less floor. This suggests that probabilistic models should be utilized to describe the motions of

fluid flow. Fluid flow field in normal conditions can be caused by an air conditioner, regions heated by sunlight, or plain noise. Probabilistic models are established for fluid flows at each point in both normal cases and abnormal cases, in which fluid flows in normal cases are used as a priori information. Then we use Bayesian principle to determine the probability of a fluid flow at a point caused by thermal abnormality.

2 Methods

The results of refractive flow computation is a flow vector $\bar{u} = (u_x, u_y)$ for each pixel in the image, corresponding to the motion of fluid flow in 3D space. Since a rise of temperature would cause the motion of fluid flow field to change locally, vector \bar{u} can be used as a feature to detect this change. The appearance of foreground leads to changes in probability density function of \bar{u} at corresponding points, and the probability of a point belonging to the foreground can be computed by Bayesian principle.

2.1 Fluid Flow Computation

The method of fluid flow field computation is shown briefly here. Please refer to [4] for detailed derivation. Denote intensity features in image sequences as $I(x, y, t)$. First, wiggle features are extracted as in (1):

$$\tilde{v} = \arg \min \sum_x \alpha_1 \|I_x v_x + I_y v_y + I_t\|^2 + \alpha_2 \left(\left\| \frac{\partial v}{\partial x} \right\|^2 + \left\| \frac{\partial v}{\partial y} \right\|^2 \right). \quad (1)$$

where I_x, I_y , and I_t are first derivatives of intensity with respect to horizontal axis, vertical axis and time respectively. Then fluid flow is computed based on the wiggle consistency assumption:

$$\tilde{u} = \arg \min \sum_x \beta_1 \left\| \frac{\partial \tilde{v}}{\partial x} u_x + \frac{\partial \tilde{v}}{\partial y} u_y + \frac{\partial \tilde{v}}{\partial t} \right\|_{\Sigma_v}^2 + \beta_2 \left(\left\| \frac{\partial u}{\partial x} \right\|^2 + \left\| \frac{\partial u}{\partial y} \right\|^2 \right) + \beta_3 \|u\|^2. \quad (2)$$

where $\|x\|_{\Sigma}^2 = x^T \Sigma^{-1} x$ and Σ is the covariance matrix of wiggle features.

2.2 Foreground Fluid Flow Detection

In this section, Bayesian principle is used to determine the possibility of a point belonging to foreground. Denote the condition without thermal abnormality as B , and a priori distribution of fluid flow at one point as $p(u|B)$. For an image sequence under an unknown condition, we compute joint possibility density function $p(u)$ for each point, because a priori model for fluid flow can be hard to determine under different depths and temperatures. Then the posterior possibility of a point belonging to the background is:

$$P(B|u) = \frac{p(u|B) \cdot P(B)}{p(u)} \quad (3)$$

where $P(B)$ is used to normalize the ratio to the interval $[0,1]$.

When the probability of a point belonging to the background is lower than a certain threshold, the pixel is classified as a point of abnormal region. In the experiments the threshold is set to be 0.15. Additionally, the two components of the fluid flow vector are judged separately, and the vector is classified as a foreground only when the two components are both under threshold.

Figure 1 shows an example of possibility density curves at one point classified as abnormal. The graph in Fig.1(a) indicates that most values of v_y fall in the interval $[-0.1,0.1]$ under the normal condition, while the values of v_y distribute in a wider range when there is abnormality, as shown in Fig.1(b). Fig.1(c) is the conditional probability of v_y of the point belonging to the background in terms of the probability density functions under two conditions. For a threshold of 0.15, it suggests that for values of v_y under -0.1, the point is classified as abnormal.

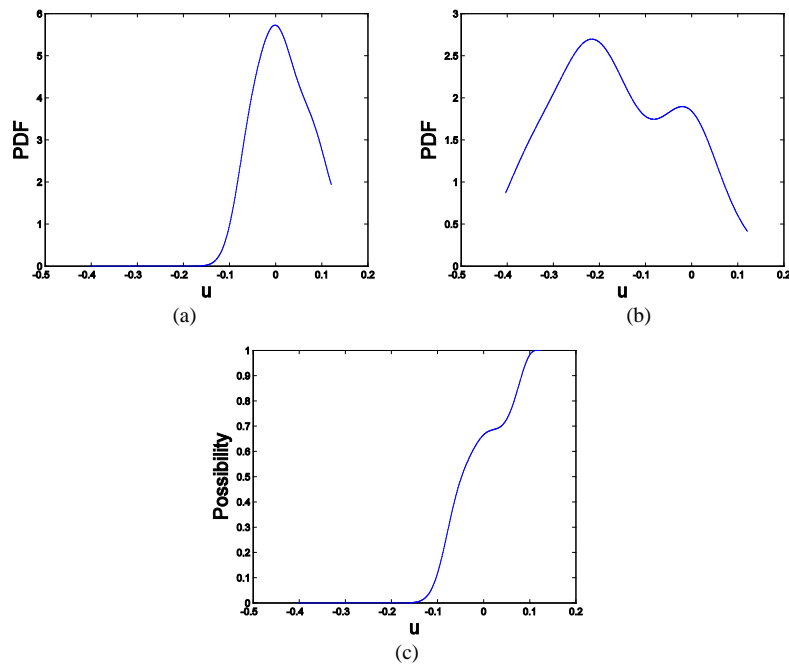


Fig. 1. (a)PDF of v_y under a normal condition; (b)PDF of v_y under an unknown condition; (c)Bayesian conditional probability of the point to be normal.

2.3 Estimation of Probability Density Function

The method used for estimating probability density functions in (3) is non-parametric

kernel density estimation. The advantage of this method is that it estimates distribution directly from sample data, without having to make an assumption about the distribution model that fluid flow is subjected to.

Suppose the sample fluid flow series at a point is $U = \{u_i\}_{i=1,2,\dots,n}$, then the estimated pdf is:

$$\hat{p}(u) = \frac{1}{n} \sum_{i=1}^n K(u - u_i) . \quad (4)$$

where $K(x)$ is the kernel function. In this paper, a Gaussian kernel with a bandwidth σ of 0.8 is adopted. To avoid possibilities become infinite or zeros appear on denominators, the range of fluid flow should be consistent with that in the unknown condition.

3 Experiments

The camera for recording image sequences is Xiaoyi2 home security camera (frame rate 25fps, resolution 1920*1080). Computations are performed on Matlab2014a. In the pre-processing step, a temporal median filter is adopted to ensure temporal consistency and prevent the flickering effect. Also used is a temporal band-stop filter to remove intensity variations from the light due to AC power. Munsell color encoding is used to visualize abnormal regions. Results for two examples are given in the following.

In kettle series, a kettle is placed 5 meters away from the camera. Image sequences are recorded before and after heating. Note that we place it for a minute to avoid the interference of steam. Results are shown in Fig.2. The white regions in Fig.2(b) represent foreground. The probabilistic method can reduce the impact of other fluid flow to a large extent, yet there still exists erroneous classified regions. One possible reason is that an extremely small flow vector would also lead to the possibility lower than the threshold. Since local heat source typically increases local fluid velocity, the values of fluid flow can be another criterion for classification in further studies.

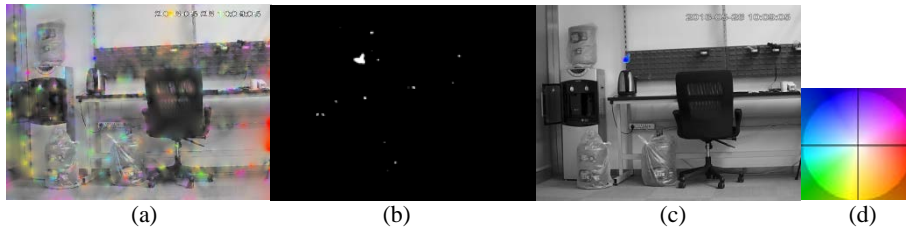


Fig. 2. Results for kettle series. (a)Fluid flow field with thermal abnormality; (b)Mask of abnormal regions; (c)Visualization of detection results; (d)Munsell color encoder

In candle series, we attempt to detect the therm given by an extinguished candle 3 meters away from the camera, as shown in Fig.3. The candle is also placed for a while to avoid interference of smoke. Another fact observed is that in both series, the target

regions appear in the color of blue, indicating fluid flow caused by thermal abnormality follows an approximately uniform direction upwards.

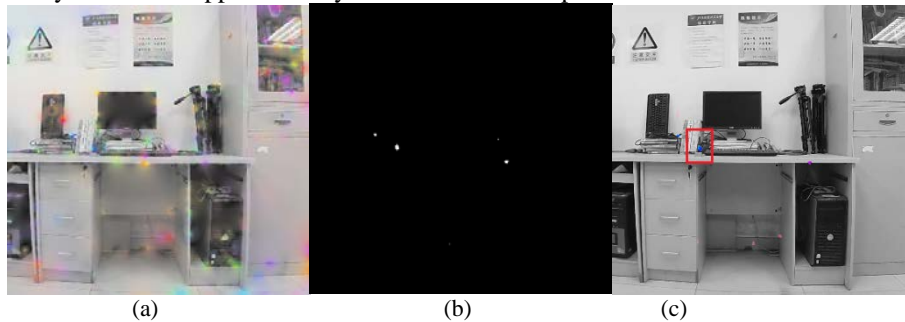


Fig. 3. Results for candle series. (a)Fluid flow field with thermal abnormality; (b)Mask of abnormal regions; (c)Visualization of detection results. The red square is added manually.

4 Conclusion and Future Work

In this paper, we attempt to detect thermal abnormality from multiple videos by detecting fluid flows caused by heat sources. To address the problem of interference by other fluid flows intrinsic to the scene, probabilistic models are introduced to compute the probability of a point to be abnormal. This method can largely reduce the impact of other fluid flows and make the target regions explicit, but still needs improvement on reducing erroneous classifications.

Further studies may introduce more complicated features other than the value of two vector components, based on a priori information such as the orientation of flow vectors and lower limitation of fluid flow velocity. The method of connected component analysis between frames can also be used to increase robustness to noise.

References

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