ISSN (Online) : 2319 – 8753
ISSN (Print) : 2347 - 6710

International Journal of Innovative Research in Science, Engineering and Technology

An ISO 3297: 2007 Certified Organization, Volume 3, Special Issue 1, February 2014

International Conference on Engineering Technology and Science-(ICETS'14)
On 10th & 11th February Organized by

Department of CIVIL, CSE, ECE, EEE, MECHNICAL Engg. and S&H of Muthayammal College of Engineering, Rasipuram, Tamilnadu, India

Detection of Flames Using Videos by Expectation Maximization and Flow Estimation Algorithm

Sasirekha.SP[1], ChinnuThomas[2], P. Dhivya[3], P.Sathyashrisharmila[4]
Department of Computer Science and Engineering, Adithya Institute of Technology, Coimbatore, India[1, 2, 3, 4]

ABSTRACT: **Automatic flame detection using real time vision-based method has drawn potential significance in last decade. The very interesting dynamics of flames have motivated the use of motion estimators to distinguish fire from other types of motion. Since fire is a complex but unusual visual phenomenon, employs distinctive parameters such as color, motion, shape, growth, dynamic texture and smoke behavior, this paper proposes expectation maximization (EM) algorithm and flow estimation, enables parameter estimation in probabilistic models with incomplete data. The expectation maximization algorithm alternates between the steps of guessing a probability distribution over completions of missing data given the current model (known as the E-step) and then reestimating the model parameters using these completions (known as the M-step). Discrimination between fire and non-fire motion can be easily determined from the flow estimation. Our approach is capable of detecting fire reliably. Moreover it drastically reduces the false alarms.**

Keyword*:* **Real-time fire detection, Flow estimation, Expectation Minimization**

I. INTRODUCTION

The traditional method to detect fire is employing some people as inspectors, human resource is expensive and they have very low efficiency. Fire sensors have already been used as another method to detect the particles generated by smoke or fire, temperature, relative humidity, etc. But they must be placed in the proximity of fire or their detecting range is usually exceeded, and the approach fails to supply the information about the process of burning, such as fire location, size, growing rate, and so on.

Most of the methods and conventional systems used in areas that need fire protection, are for indoors, and their mechanical systems are designed to detect not the most of those systems. Alarm is not issued unless particles reach the sensors to activate them. Also, infrared and ultraviolet sensors that are also commonly used produce many false alarms. By the help of machine vision techniques, it is possible to get better results than conventional systems because images can provide more reliable information. With the faster and faster urbanization process, more and more high-rise buildings appear around us. This also can make the frequency of fire increase and bring great losses to people's lives and property. As the damage caused by fires is so tremendous that the early fire detection is becoming more and more important. Recently, fire detectors have been used in many place, they used the smoke, temperature and photosensitive characteristics to detect fires. But they are too worse to meet the needs in a large space, harsh or the outdoor environment. Video surveillance is widely used in commercial and military fields such as traffic and portable applications. Automatic fire detection in images and videos is crucial for early fire detection which can solve the aforementioned problem. Video-based systems can detect uncontrolled fires at an early stage before they turned in to disaster

This paper is organized into five sections. The section-2 gives the overview of fire and flame detection using videos. The survey of literature and its related work have briefly studied in the section-3. Followed by, the section-4 suggests an effective approach for fire detection. Finally, it is concluded in the section-5.

II. OVERVIEW OF FLAME DETECTION USING VIDEOS

Detecting, segmenting, recognizing, and classifying dynamic textures can rely on visual aspects such as geometry or motion, or both. The current methods of analysis are based on optical flow estimation and

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geometric. Moving objects' estimation is often used to segment the possible fire region from video sequence, and traditional algorithms include consecutive frame and background subtraction. Transient change of image can be detected, but the overlapping region of two consecutive frames can be mistakenly taken as background.

A. Model for extracting fire region

In the algorithm of background subtraction, intact target region can be extracted because of the static state of the background image, but the extracted target may be vague and inaccurate if the background image cannot be updated in time. In most cases, it is difficult to contain a forest fire beyond 15 minutes and rapid detection is therefore critical. To assist human surveillance, infrared technology has been proposed to detect forest fire with thermal infrared cameras. Until now, these methods do not yield good results for the main reason that the fire itself is often hidden by the trees. For forest environment, the whole scene does not keep still due to waving trees, changing weather, varying light, moving shadow, shaking camera, and so on. Therefore, compared with moving estimation, color based segmentation is suitable for forest fire extraction. Each detector ensures the basic functions of smoke detection and data transmission. When fire detection occurs on a particular remote analyzer, alarm position on a map and fire images are sent to the control station to obtain quick visualization and the location of the growing blaze.

B. Separation of noise from target region

An important issue in automatic fire detection is separation of fire sources from noise sources. Dynamic textures, for example fire and smoke, flowing water, or foliage blown by the wind, are common in natural scenes. However, in many cases only parts of the scene form dynamic textures. In addition, their spatial extent can keep varying and they might be partially transparent, which makes it difficult to separate them from a textured background. Due to these problems the geometry (size and shape) can be misleading. The difference in dynamics, however, could be successfully employed to detect and segment them. Motion estimators are usually built on the brightness constancy assumption. Under this assumption an object's brightness is constant from frame to frame. This assumption holds for rigid objects with a surface, but fails for fluid and gaseous materials which are typical for dynamic textures. Dynamic textures are usually defined by extending the concept of self-similarity, well-established for static textures to the spatiotemporal domain. Weak dynamic textures such as a simple moving texture are covered by this definition.

In these dynamic textures, there exists a local moving coordinate system in which the texture becomes static. This local coordinate system can be computed using standard optical flow algorithms relying on the brightness constancy assumption, strong dynamic texture, possessing intrinsic dynamics; these cannot be captured by this approach because of self-occlusion, material diffusion, and physical process not obeying the brightness constancy assumption. The brightness of an image point in one frame can propagate to its next frame. A static or weak dynamic texture obeys the brightness constancy assumption, and dynamic texture is better modeled by the brightness conservation. The scheme segmentation is used for detecting dynamic texture regions based on their specific motion characteristics. Ambient intelligence is a digital environment that is responsive and adaptive to human presence. Within a home environment ambient intelligence can improve the quality of life by creating a functional, personalized inter-connected system, services and technologies are expected to combine ubiquitous computing and intelligent systems putting humans in the centre of technological developments. Today's many intelligent systems utilize forms of inputs from video cameras. The basic usage is motion estimation and fire detection.

C. Fire And Its Properties

Typically, fire comes from a chemical reaction between oxygen in the atmosphere and some sort of fuel. For the combustion reaction to happen, fuel must be heated to its ignition temperature.
In a typical wood fire:

1. First something heats the wood to a very high temperature. When the wood reaches about 150 degrees Celsius, the heat decomposes some of the cellulose material that makes up the wood. Some of the decomposed material is released as volatile gases.
2. We know these gases as smoke. Smoke is compounds of hydrogen, carbon and oxygen. The rest of the material forms char, which is nearly pure carbon, and ash, which is all of

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the unburnable minerals in the wood (calcium, potassium, and so on). The char is also called charcoal. Charcoal is wood that has been heated to remove nearly all of the volatile gases and leave behind the carbon. That is why a charcoal fire burns with no smoke.

The actual burning of wood then happens in two separate reactions:

1. When the volatile gases are hot enough (about 260 degrees C for wood), the compound molecules break apart, and the atoms recombine with the oxygen to form water, carbon dioxide and other products. In other words, they burn.
2. The carbon in the char combines with oxygen as well, and this is a much slower reaction. A side effect of these chemical reactions is a lot of heat. The fact that the chemical reactions in a fire generate a lot of new heat is what sustains the fire. As they heat up, the rising carbon atoms emit light. This "heat produces light" effect is called incandescence. It is what causes the visible flame.
3. Flame color varies depending on what is being burned and how hot it is. Color variation within in a flame is caused by uneven temperature. Typically, the hottest part of a flame glows blue, and the cooler parts at the top glow orange or yellow. The dangerous thing about the chemical reactions in fire is the fact that they are self perpetuating. The heat of the flame itself keeps the fuel at the ignition temperature, so it continues to burn as long as there is fuel and oxygen around it.
4. The flame heats any surrounding fuel so it releases gases as well. When the flame ignites the gases, the fire spreads. On Earth, gravity determines how the flame burns. All the hot gases in the flame are much hotter than the surrounding air, so they move upward toward lower pressure. This is why fire typically spreads upward, and it's also why flames are always "pointed" at the top.

III. SURVEY OF LITERATURE

Automatic fire detection is important for early detection and promptly extinguishing fire. Several decades of forestry research have resulted in many advances in field of forest fire monitoring. There are many ways to monitor forest fires. Traditionally, some personnel in a lookout tower located in a high point performed the monitoring tasks .This method of monitoring is still used in some countries such as US, Canada, and Australia (Towers). Due to difficult life condition at lookout towers and unreliability of human observations, some vision techniques such as Automatic Video Surveillance Systems (AVSS) were proposed to monitor small forests. Author in paper [1] survived about fire detection in residential areas ION detectors are advantageous for flaming fire detection, while photo detectors are beneficial for non flaming fire detection. To achieve more reliable and fault-tolerant results and higher detection rates more than one sensor should be used. This assures that flaming and non flaming fires can be discriminated.

In paper [2] author suggest a method to detect fire time by processing the video data generated by an ordinary camera monitoring a scene. For motion and color clues, fire flicker is detected by analyzing the video in the wavelet domain. Improper periodic behavior in flame boundaries is detected by performing temporal wavelet transform. Color variations in flame regions are detected by computing the spatial wavelet transform of moving fire-colored regions.

In paper [3], [5], authors proposed a algorithm uses YCbCr color space to separate the luminance from the chrominance more effectively than RGB. Author in paper [3], used a rule-based generic color model for flame pixel classification is suggested. The performance tested on image contains fire, and image containing fire-like regions. This method has shown a higher detection rate and a lower false alarm rate. The arithmetic operation for the color model is linear with image size and algorithm is very cheap in computational complexity. Color model can be used in fire detection in video sequences.

Author in paper [5], used fuzzy logic enhanced generic color model for fire pixel classification, and it is used to replace existing heuristic rules and make the classification more robust in effectively discriminating fire and fire like colored objects. Further discrimination between fire and non fire pixels are achieved by a statistically derived chrominance model which is expressed as a region in the chrominance plane. The decision for classifying a fire pixel can be made combining the mask derived from fuzzy logic enhanced luminance model with the chrominance model.

In paper [4], author proposed a method that combines foreground object information with color

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pixel statistics of fire. Adaptive background model of the scene is generated by using three Gaussian distributions, where each distribution corresponds to the pixel statistics in the respective color channel. The foreground information is extracted by using adaptive background subtraction algorithm, and then verified by the statistical fire color model to determine whether the detected foreground object is a fire candidate or not. A generic fire color model is constructed by statistical analysis of the sample images containing fire pixels. This method process with segmentation of the fire candidate pixels from the background, then a generic statistical model for refined fire-pixel classification is processed. Then the two processes are combined to form the fire detection system and applied for the detection of fire in the consecutive frames of video sequences. Color information of fire is determined by the statistical measurement of the sample images containing fire. The foreground objects detected are combined with color statistics and output is analyzed in consecutive frames for fire detection. The system detects the fire as soon as it is started, except in the explosive conditions, in which generally smoke is seen before the fire is started. This algorithm extended to incorporate the smoke in the video sequences, which may be used as faster fire alarm detection.

Author in paper [6], proposed automatic forest fire detection from video, based on 3D point cloud of the collected sample fire pixels, Gaussian mixture model is built and helps segment possible flame regions in image. Then the flame pattern is defined for forest, and three types of fire colors are labeled with 11 static features including color distributions, texture parameters and shape roundness, the static SVM classifier is trained and filters the segmented results. Using overlapping degree and varying degree, the remained candidate regions are matched among consecutive frames. The variations of color, texture, roundness, area, and contour are computed, and then average and the mean square deviation of them are obtained. This approach recognizes the fire like objects, such as red house, bright light and flying flag.

Color based segmentation and color distribution, is very helpful for classification. For the segmented results, SVM trained on static features is applied to filter out the false regions. To compute the fire flickering frequency based on region contour, the temporal wavelet is used to analyze Fourier descriptors representing the variation of flame contour in a short period.

Author in paper [7], suggests a method for detecting regions of dynamic texture in image sequences and motion estimation is usually based on the brightness constancy assumption. This assumption holds well for rigid objects with a Lambertian surface, but it is less appropriate for fluid and gaseous materials. For these materials a variant of this assumption, which we call the brightness conservation assumption should be employed. Under this assumption an object's brightness can diffuse to its neighborhood. Segmentation into regions of static and dynamic texture is achieved by using a level set scheme. The level set function separates the images into areas obeying brightness constancy and those which obey brightness conservation.

Author in paper [8], computer vision-based fire detection algorithms are usually applied in closed-circuit television surveillance scenarios with controlled background. This method can be applied not only to surveillance but also to automatic video classification for retrieval of fire catastrophes in databases of newscast content. There are large variations in fire and background characteristics depending on the video instance, and then analyze the frame-to-frame changes of specific low-level features describing potential fire regions. The features are color, area size, surface coarseness, boundary roughness, and skewness within estimated fire regions. Because of flickering and random characteristics of fire, these features are powerful discriminates. The behavioral change of these features is evaluated, and the results are then combined according to the Bayes classifier for robust fire recognition. This method exploited visual features of fire, like boundary roughness and skewness. The skewness is a very useful descriptor because of the frequent occurrence of saturation in the red channel of fire regions.

The proposed approach is a combination of expectation maximization algorithm and flow estimation. It enables parameter estimation and optimal mass transport models fire with dynamic texture, and the features related to the flow magnitudes and directions are computed from the flow fields to discriminate between fire and non-fire motion.

IV. PROPOSED APPROACH

The proposed approach is capable of detecting fire reliably. Moreover it drastically reduces the false alarms.

IJIRSET

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A. Expectation Maximization

Mainly EM is used to image segmentation and it assumes the image pixels or feature vectors as a mixture model.

Expectation Maximization algorithm enables parameter estimation in probabilistic models with incomplete data. It computes probabilities for each possible completion of the missing data, using the current parameters. These probabilities are used to create a training set consisting of all possible completions of the data. Then maximum likelihood estimation deals with training set and provide the confidence of the model in each completion of the data (the expectation maximization algorithm alternates between the steps of guessing a probability distribution over completions of missing data given the current model (known as the E-step) and then reestimating the model parameters using these completions (known as the M-step). The name 'E-step' comes from the fact that one does not usually need to form the probability distribution over completions explicitly, but rather need only compute 'expected' sufficient statistics over these completions. Similarly, the name 'M-step' comes from the fact that model reestimation can be thought of as 'maximization' of the expected likelihood of the data.

B. Flow Estimation

The key idea consists of exploiting the difference between the turbulent, fast, fire motion, and the structured, rigid motion of other objects. The first is the optimal mass transport (OMT) optical flow for modeling dynamic textures such as fire. Second is a non-smooth optical flow model for rigid motion. The features extracted from the optical flow fields for classification. Those features include quantities related to the flow magnitude and the flow directions. Then, auxiliary concepts of candidate regions and proposes to train a neural net (NN) for fire detection.

Optical flow estimators, on the other hand, transform the image sequence into estimated motion fields, allowing for a more insightful extraction of features. Optical flow algorithms are analyzed for the recognition of various dynamic textures. This algorithm improves robustness to rigid motion of fire-colored objects and unfavorable backgrounds, which tend to cause many false detections in current systems.

1. Optical Flow is Target-specific, Structure preserving, from one flow field from two flow fields
2. Classification Recognition of textures Detection of flames

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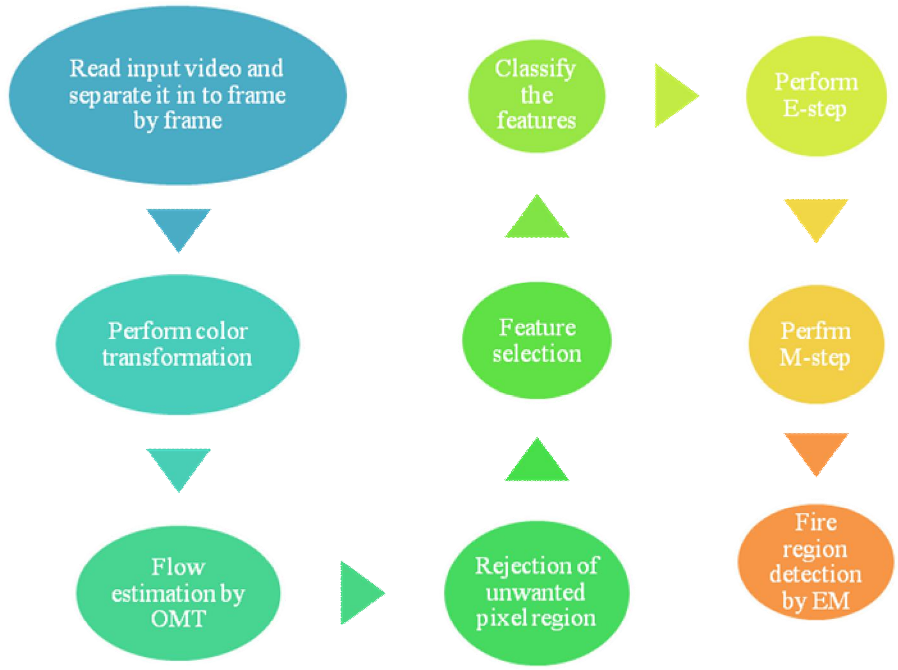

Figure 1 Flow of the algorithm

OMT-Optimal Mass Transport (Discrimination between fire and non-fire motion)

E-Expectation (probability distribution over the current region)

M-Maximization (reestimate the parameters)

1) Optimal mass transport

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.

Classical optical flow models based on brightness constancy are inadequate to model the appearance of fire for two reasons

First, fire does not satisfy the intensity constancy assumption, 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 and motion field.For these reasons, an optical flow estimation modeling fire as a dynamic texture, the optimal mass transport (OMT) .

2) Non smooth data

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. Novel optical flow energy functional called Non-Smooth Data optical flow (NSD).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. The flow of vector regularizes the flow magnitude, but does not enforce smoothness. This choice makes the NSD flow directions purely driven by the data term under the constraint that flow magnitudes are not too large. While this method is not

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expected to perform well for standard optical flow applications where flow smoothness plays an important role, it is useful for detecting saturated fire.

V. CONCLUSION

The very interesting dynamics of flames have motivated the use of expectation maximization and motion estimators to distinguish fire from other types of motion. Two optical flow estimators, OMT (optimal mass transport) and NSD (non-smooth data), are used to overcome insufficiencies of classical optical flow models when applied to fire content. The obtained motion fields provide useful space to define motion features. These features reliably detect fire and reject non-fire motion. EM starts with an initial guess of the parameters. In the E-step, a probability distribution over possible completions is computed using the current parameters. Then in M-step it updates the parameter estimation. EM is used to reduce false detections.

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