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A Survey about Automatic Flame/Fire Detection in Videos

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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. Discrimination between fire and non-fire motion can be easily determined. There are many different approaches are available to detect fire at the early stage. This paper propose a survey about automatic fire detection in videos this survey provide a way to learn about different algorithms used for early fire detection, main problem in automatic fire detection is separation of fir sources from noise sources. Traditionally different combination of fire detection methods is used in industries, companies', and commercial malls to detect fire. Automatic fire detection prevents fire scattering and huge damage.

Keyword: Automatic fire detection; fire detection in videos; vision-based method; fire detection technologies

1. 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 fire itself but its byproducts. The presence of certain particles generated by smoke and fire is detected by 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.Traditional fire detection technologies are explained in section-3.Followed by, the applications and advantages are discussed in section-5. Finally, it is concluded in the section-6.

2. 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 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.

2.1. 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.

2.2. Segmenting fire source from other sources

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.

2.3. 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 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 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.

2.4. Issues

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. However, a strong dynamic texture, possessing intrinsic dynamics, cannot be captured by this approach because of self-occlusion, material diffusion, and other physical process not obeying the brightness constancy assumption. The brightness of an image point (in one frame) can propagate to its neighborhood (in the next frame). While a static or weak dynamic texture obeys the brightness constancy assumption, strong dynamic texture is better modeled by the brightness conservation assumption. Segmentation scheme 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, inter-connected, personalized systems and services. Technologies are expected to combine concepts of 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.

3. 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 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.

4. FIRE DETECTION TECHNOLOGIES RATHER THAN VIDEOS

4.1. Particulate Sensing

Smoke detectors sense the aerosol produced from flaming this type of sensors called spot detectors. There are many different techniques to detect particulates in the air Particulates may vary due to its physical properties it may be dust, smoke or condensed vapor and to discriminate between these physical properties and reduce false alarm different methods are used in sensors.

4.2. Thermal Environment Sensing

Thermal energy is radiated from the fire and the fire can be detected by observing changes in the thermal environment, the sensor sense through rise in temperature. The temperature sensor and smoke sensor are combined this provide a effective sensor.

4.3. Radiation Sensing

Flaming Fire emit radiation over a broad band of wavelength. UV(ultra violet) and IR(Infra red) radiations are emitted from many flames. The radiation sensor must be within the line-of sight of the fire.

4.4. Chemical Sensing

Fire produce gaseous byproducts and it is the basis for detection. Chemicals in the fire is useful for detect fire at early stage it includes CO_2, H_2O, CO, H_2. Chemical sensing is potentially beneficial in improving detection and reducing false alarms

Types of chemical sensors,

- Catalytic gas sensors
- Semiconductor gas sensors
- Electro-chemical and Mechanico-chemical sensors.

5. APPLICATION AND ADVANTAGES

5. 1. Application

Automated surveillance for security-conscious venues such as airports, casinos, museums, and government installations: Intelligent software could monitor security cameras and detect suspicious behavior. Automated surveillance increases the productivity of the human operator and coverage of the surveillance.

1. Human interaction with mobile robotics: Autonomous mobile robots in the workplace or home could interact with the humans around them if they could reliably detect their presence.
2. Safety devices for pedestrian detection on motor vehicles: Intelligent software on a camera-equipped car could distinguish pedestrians and warn the driver.
3. Other applications include athlete training, clinical gait analysis, traffic monitoring.
4. Useful in real life applications is a camera that can track a person of interest on a dynamic and realistic background.
5. Detection of fire is a particularly serious problem in situations of congested automobile traffic, naval vessels, and heavy industry.
6. 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.
7. Surveillance cameras have become pervasive, installed by governments and businesses for applications like license-plate recognition and robbery deterrence.

5.2. Advantages

The advantages of fire detection technology based on the video image,

1. Fire detection techniques are very intuitive.
2. Due to the speed of light transmission and induction is far higher than the smoke and temperature, such fire detection with high real-time has no delay caused by induction time.
3. The remote surveillance cameras can be adjusted freely and not to be confined to the indoor and outdoor space. So its detection range is larger other methods.
4. The image can save more scene information through color and texture, which promotes the diversification of the fire detection method greatly.
5. It is convenient for people to verify or record or query the fire with the saved video monitor screen, so this technology has a higher reliability and real-time performance.
6. Enhanced Protection: An integrated solution can help optimize system performance and functionality, thereby enhancing your life safety and property protection program.
7. Data Integrity and Protection: Today's sophisticated IT and data security capabilities are absolutely critical when fire, emergency communications, security and other life-safety systems are integrated.

6. CONCLUSION

A survey on different methods used to detected fire using videos in real time has been. As fire should be put out early in order to prevent spreading, the speed of the fire detection system is important, this survey provides information about different methods used for early fire detection and how they process after fire detection and indicates the fire. The main disadvantage of smoke detectors are their response time is slower, as it requires smoke and heat to dissipate. This makes the video based detector a very viable replacement for these systems, as it eliminates the weaknesses of current smoke detectors. Video base smoke detectors are also available. Automatic flame detection in videos provides efficient way to detect fire in closed as well as open space. The technology can even be merged with other technologies, and work in conjunction with other systems.

References

[1] Majid Bahrepour, Nirvana Meratnia, Paul Havinga, A survey from wireless sensor network perspective, *in Proc. IEEE Int. Conf. Image Process, 2010.*

[2] B. Ugˇur To¨reyin a, Yigˇithan Dedeogˇlu b, Ugˇur Gu¨du¨kbay b, A.Enis Cetin a, Computer vision based method for real-time fire and flame detection, *in Proc. IEEE Int. Conf. Image Process, 2008.*

[3] T. C- elik, H. Demirel, Fire detection in video sequences using a generic color model, Fire Safety Journal (2008),*doi:10.1016/j.firesaf.2008.05.005*

[4] Turgay Celik , Hasan Demirel, Huseyin Ozkaramanli, Mustafa Uyguroglu "Fire detection using statistical color model in video sequences" , *Springer, 2009.*

[5] Çelik*, Hüseyin Özkaramanl, Hasan *Demirel*, Fire Pixel Classification Using Fuzzy Logic And Statistical Color Model, Department of Electrical and Electronic Engineering, Eastern Mediterranean University,Gazimağusa, TRNC, Mersin 10, TURKEY, **turgay.celik@emu.edu.tr1424407281/07/$20.00 ©2007 IEEE*

[6] Jianhui Zhao, Zhong Zhang, Shizhong Han, Chengzhang QuZhiyong Yuan, and Dengyi Zhang**,** SVM Based Forest Fire Detection Using Static and Dynamic Features**,** Computer School, Wuhan University, Wuhan, Hubei, 430072, *PR China jianhuizhao@whu.edu.cn, DOI: 10.2298/CSIS101012030Z*

[7] Tomer Amiaz1, S´andor Fazekas, Dmitry Chetverikov, and Nahum Kiryati1,School of Electrical Engineering Tel Aviv University Tel Aviv, Israel Computer and Automation Research Institute Budapest, Hungary F. Sgallari, A. Murli, and N. Paragios, "Detecting Regions of Dynamic Texture" , *Springer-Verlag Berlin Heidelberg ,2007.*

[8] Paulo Vinicius Koerich Borges, Member, IEEE, and Ebroul Izquierdo, Senior Member, IEEE"A Probabilistic Approach for Vision-Based Fire Detection in Videos", Circuits and Systems for Video Technology, *IEEE Volume: 20, May 2010*.

[9] Huaiqin Qi, Yiman Zhao and Gang Xu , Research of Angular Detection Algorithm in the Fire Flame Based on the SUSAN Operator , Department of Communication and Electronic Engineering University of Qiqihar Qiqihar, Heilongjiang Province, China,*2012 IERIA.*

[10] Wen-Bing Homg, Jim-Wen Peng, and Chih-Yuan Chen, New Image-Based Real Time Flame Detection Method Using Color Analysis, *2005 IEEE.*

[11] A.K. Singh Department of Electronics Engineering IIIT Allahabad, India and Harshit Sing Department of Information Technology IIIT Allahabad, India, Forest Fire Detection through Wireless Sensor Network using Type-2 Fuzzy System, International Journal of Computer Applications (0975 – 8887) *Volume 52– No.9, August 2012*.

[12] Prof. K.Angayarkkani D.G. Vaishnav College and Dr.N.Radhakrishnan Geocare Research Foundation, Chennai, India, Efficient Forest Fire Detection System: A Spatial Data Mining and Image Processing Based Approach, IJCSNS International Journal of Computer Science and Network Security, *VOL.9 No.3, March 2009.*

[13] B. Uˇgur T¨oreyin, Yiˇgithan Dedeoˇglu, A. Enis C¸ etin, Flame Detection In Video Using Hidden Markov Models,Bilkent University, TR-06800 Bilkent, Ankara, Turkey.

[14] Ziyou Xiong, Rodrigo Caballero, Hongcheng Wang, Alan M. Finn, Muhidin A. Lelic,and Pei-Yuan Peng, Video-based Smoke Detection: Possibilities, Techniques, and Challenge, United Technologies Research Center, East Hartford.