ISSN 2249-6343
International Journal of Computer Technology and Electronics Engineering (IJCTEE)
Volume 3, Special Issue, March-April 2013, An ISO 9001: 2008 Certified Journal.
E-NSPIRE, A National Level Conference held at Pravara Rural Engineering College, Loni, Maharashtra, INDIA.

Efficient Visual Fire Detection Applied For Image

D. B. Rane, Khairnar Jidnyesh K, Kachava Atul A, Shinde Vasant N

Abstract- The specific challenge of this project is to build a computer controlled Robot that can move through a model floor plan structure of a house, find a lit candle and then extinguish it in the shortest time subject to a few operating factors [...]. This is meant to simulate the real-world operation of a Robot performing a fire protection function in an actual home. The candle represents a fire which has started in the home which the Robot must first find and then extinguish. In this project we use a combination of techniques to detect fire in video data. First, the algorithm locates regions of the video where there is movement. From these regions fire colored pixels are extracted using a perception. Lastly, we use dynamic texture analysis to confirm that these moving, fire-colored regions have the temporal and motion characteristics of fire.

I. INTRODUCTION

Fire incidents can cause loss of lives and damage to property. Damage due to fire has always been a major area of concern for museums, warehouses, and residential buildings. Conventional fire detection sensors (e.g., ionization and photoelectric detectors) and fire sprinkler systems monitor only particular points in space. In most cases, conventional point-type detectors are installed on walls or on a ceiling. The delays in the activation of fire detection sensors and sprinklers in large spaces are a major problem. Hence, the monitoring capabilities of point-type sensor devices are limited to a certain distance, and they are ineffective for monitoring large areas. These devices are not sufficiently flexible to detect fire incidents, and many fire-detection sensors and sprinklers are required to be installed very close to the monitoring areas. Comparatively, the video camera is a volume sensor, and potentially monitors a larger area and has a much higher probability of successful early detection of fire flames. Video surveillance technology is suitable for early detection of fires due to its low detection delay, good resolution, and high localization accuracy [2]. Early detection of fires can certainly expedite fire-fighting efforts, and consequently, fires can be extinguished before they spread to other areas. To monitor large spaces, the use of a mobile fire-fighting robot is a more flexible alternative than installing a large number of detectors and sprinklers. When a fire is detected, the fire-fighting robot can move to the position of the fire flame and safely evacuate an object from the fire area. Automatic fire detection devices have been around since the first smoke alarm was invented by Francis Upton in 1890 [5]. After further technological advances in the mid 1960s reduced the price of smoke detectors, these devices started showing up in buildings all over the world, becoming the ubiquitous and essential devices that they are today [5].

Fig .1An Autonomous Airship and a Helicopter

Monitoring a fire in them COMETS experiments carried out in Lousa (Portugal). [3] However, automated fire detection devices such as smoke detectors have some significant limitations which make them useless in many important situations. For instance, smoke detectors, the most common type of fire detection device, only work well in small enclosed spaces like those find in homes and offices. However, in large open spaces such as warehouses, atriums, theaters, and the outdoors, smoke detectors are ineffective because they require smoke to build up to sufficient levels to set them off. In open spaces, the fire is usually out of control by the time smoke has built up sufficiently to set off the alarm. Heat sensors suffer from the same shortcomings as smoke detectors. Video-based fire detection does not suffer from the space constraints that smoke and heat detection do. Cameras can detect and pinpoint fire from long distances as soon as the fire starts, allowing the fire to be dealt with before it gets out of control. Furthermore, cameras can cover very large areas, potentially mitigating their high cost compared to other fire detection technologies. Video-based fire detection even has the potential to be placed on mobile platforms such as planes and robots.

OUR APPROACH

Since fire is a complex but unusual visual phenomenon, we decided upon a multi-feature-based approach for our algorithm. The hope and the goal of such an algorithm is to find a combination of features whose mutual occurrence leaves fire as their only combined possible cause. Fire has distinctive features such as color, motion, shape, growth, and smoke behavior. For this project we focused on features such as color and motion and we hope to include additional feature analysis in future work. To reduce the total computational load, the first step of our algorithm is to perform frame differencing to get a rough idea where motion occurred. The regions of the video which are moving are fed to a fire color classification algorithm. There are a number of different ways of detecting fire colored pixels. In [6], the authors used a mixture of Gaussian in the RGB color space to classify pixels as being fire colored or not. In [7], pixels whose color landed in a specific segment of the HSV color space were

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classified as being fire colored. We decided to use a multilayer perception, like [8], to classify pixels as being fire colored or not. Spatial clustering and analysis is performed on the pixels that get classified as being fire colored. The next stage involves grabbing a short 50 to 100 frame sequence of the video focused and centered at each of these moving fire-colored regions. These short video sequences are then fed to a module which performs dynamic texture analysis it. The result is that the target region is either classified as being fire or not.

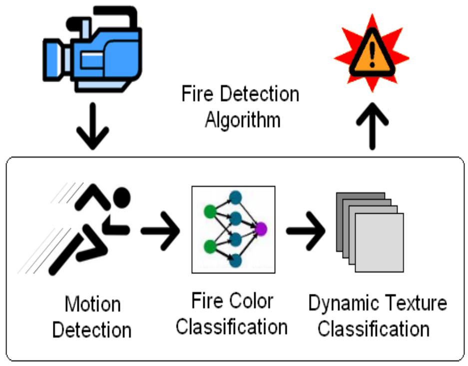

Fig 2. The Fire Detection Algorithm Outline

II. MOTION DETECTION

The first step for our algorithm is to find regions in the video stream where there is motion. This is done through frame differencing based on image intensity values. Given that flames often flicker and jump, the algorithm has a built in timer which keeps track how long it's been since there's been movement at a particular pixel. This helps 'smooth' out the results for the query, 'where is there motion in the video'.

Fig 3. Original Frame Sequence. [4]

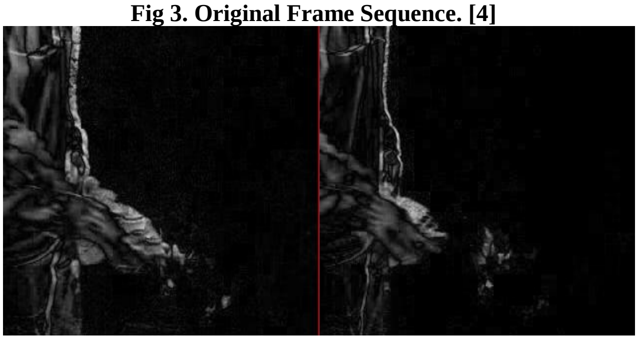

Fig 4. Motion Detected By Frame Differencing. [4]

III. DETECTING FIRE COLORED PIXELS

To classify pixels as being fire colored or not, we decided to use a multilayer perception. The perception has two layers, three input nodes for each of the color channels, and one node in the hidden layer. (Given that perceptions are well described in the literature and known in many fields, I will forgo their description here.) At first glance one might say that fire color classification fails miserably because it tends to label lots of non fire pixels as being fire. However, the goal of this first classifier is

Fig 5. Original Image. [4]

Fig.6. Red Denotes Pixels That Were Classified As Being The Color Of Fire. [4]

To get a very high true positive rate and a low false negative rate, regardless of the false positive rate. This is because the color classifier is the first in a sequence of classifiers whose job is to weed out the color classifier's false positives. Thus, these additional classification algorithms will help to reduce the overall false positive rate. One of the advantages of choosing a perception to perform color classification is that it is easy to retrain. Given that the input images might be coming from different types of cameras with different levels of saturation and different color ranges, ease of retraining is an important feature. This way, it is easy to apply this technology to existing camera systems with a minimum amount of time and difficulty.

IV. MOTION + COLOR

The follow images are the result of passing the image through the motion detection module and then passing those results through the fire-color classifier. As you can see, these combined results are much more

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Fig 7. Fire-Color Classification sans Motion Detection

Fig 8. Fire-Color Classification plus Motion Detection

Accurate than just motion or color alone. Furthermore, by only passing regions of the image that display movement, significantly fewer pixels have to get fed to the color classifier, resulting in sizable time savings. Chaining these classifiers also reduces the size and number of regions that the dynamic texture classifier has to check.

V. DYNAMIC TEXTURE ANALYSIS

The idea behind dynamic textures is that certain video sequences of moving scenes exhibit specific stationary properties [9]. Using the statistical properties of sequences such as those created by water, smoke, and fire, it is possible to create an autoregressive moving average (ARMA) model for the target image sequence. One can even use this method to recognize and segment out parts of images based on their dynamic texture characteristics as was shown in [10] and [11] respectively. In our case, we just want to recognize if a given dynamic texture is that of fire or not, since we have already determined the location of the potential fire region and thus don't need the video to be segmented.

VI. SYSTEM IMPLEMENTATION

A ALGORITHM

Start the procedure
Take the image sequence
Extract the fire pixel and smoke pixel
Check the real fire if it is not then go to second step, otherwise go to next step
Discover the fire and give the alarm.

B.FLOWCHART

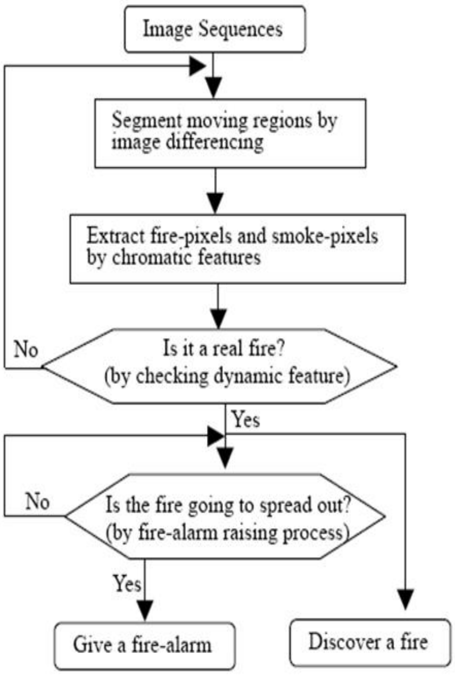

Fig 9. The Proposed Early Fire- Detection Algorithm

VII. FEATURES OF THE PROJECT

The system can give real time response in accordance to the input provided. Easy data processing or logging. The system is time saving as well as reducing the human efforts. All the features of the ARM Processors are achieved as the ARM Processor is used.

- Lower power consumption.
- The system is easy to install.
- The system gives a precise and accurate output.
- The system is highly reliable.
- The system is unaffected by environmental conditions.

VIII. APPLICATION

- Airport
- Railway
- Transportation
- Forest
- In Colleges and Schools.
- In Hospitals and Library

IX. FUTURE SCOPE

The system is used for fire detection in various applications. This technique can be used in SWARM robotics. As there is no high power device is used, the system can be implemented at the environmental conditions where the electricity is not used or negligibly used. So at these situations, the system may become highly efficient and highly reliable.

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AUTHOR'S PROFILE

Prof. D. B. Rane
dbrane_123@rediffmail.com
M.E. Electronics Engg (Digital Electronics)
Asst. Prof. , Electronics Engg.
Pravara Rural Engineering College, Loni.

Mr. Khairnar Jidnyesh K Jidnyeshk@gmail.com
B.E. Electronics Engg
Pravara Rural Engineering College, Loni.

Mr. Kachava Atul A
atulkachava@gmail.com
B.E. Electronics Engg
DEQ Pravara Rural Engineering College, Loni.

Mr. Shinde Vasant N vasantshinde123@gmail.com
B.E. Electronics Engg
Pravara Rural Engineering College, Loni.