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"Fire Detection using Optical Flow Method in Videos"

Sunita Harlapur
Mtech student, Dept. of ECE, SJBIT,
Bangalore

Dr. K. R. Nataraj
Professor and HOD, Dept. of ECE, SJBIT,
Bangalore

***Abstract*- Image processing plays an important role in real time applications such as video surveillance. Video tracking is one of the popularly growing methods of surveillance when the object is at risk. Fire detection in videos at early stage is vital for prevention of material damage and human loss. Sensors won't be able to detect the fire in its initial stage as it takes time for smoke to reach the sensors. Classical Optical flow methods are based on intensity constancy and flow smoothness. But fire is having dynamic texture and non-smoothness for saturated flames. Optical flow fields are extracted from optimal mass transport for the dynamic texture of fire and non-smooth data flow fields for saturated flames. These features are tested on large video database to detect the fire.**

Keywords: Video tracking, Surveillance, Fire detection, Optical flow.

I.INTRODUCTION

Detecting fire provides security for precious objects such as Museums, ATMs, and Banks. Nowadays security is the main issue for protecting priceless objects like gold, money, diamond, uranium. Providing safety for such objects is a tough challenge, particularly for public museums and galleries. These institutions face the conflicting dilemma of keeping objects safe, yet allowing millions of visitors a chance to see them. Home security has also become an important issue today increasing the necessity for security systems. Therefore in all cases it is important to track the objects [1] and protect the things from the fire and achieve public safety.This is a particularly serious problem in situations of congested automobile traffic, big industry and naval vessels.

The Conventional security systems include CCTV cameras, alarms and sensors to detect heat or smoke particles and are quite successful for indoor fire detection. However, they cannot be applied in large open spaces such as ships, forest area and garages. This paper presents a video-detectionapproach using optical flow method where point-sensors may fail. In addition to covering a wide viewing range, video cameras capture data from which additional information can be extracted; for example, the precise location, extent, and rate of growth. Surveillance cameras have become an important aspect in security and have become a necessity to keep proper check. There are many number of surveillance cameras are installed by governments for various applications in various fields such as license-plate recognition and robbery deterrence. Computer vision [2] based fire detection can take advantages of these cameras and can contribute to public safety.

Computer vision [3], this is the task of finding a given object in an image or video sequence. We propose the optical flow techniques to calculate the flow analysis of fire which can be used to extract the fire from the other moving objects. Optical flow is an important technique in motion analyzing for machine vision.

II.EXISTING SYSTEM

Conventional security systems for fire detection include CCTV cameras, Burglar alarms, Infrared security systems etc. One common kind of security systems is a wireless infrared security system. Infrared is very useful to cover large areas and infrared alarms work by sending out a beam of light, if this beam is broken the alarm will be sounded. The disadvantage of using infrared security systems is that they require a direct line of sight.These beams cannot pass through walls or people and limits the effectiveness of such a system in certain situations. Burglar alarms are systems designed to detect fire in a building or area. But the sensors require generation of radiations continuously which is expensive and tedious. Closed-circuit television (CCTV) cameras can't give security alert but they just capture the things, high network bandwidth requirements (IP), hacking via internet by criminals. To overcome these disadvantages we are making use of video processing which is instantaneous, more reliable and cost effective.

III.LITERATURE SURVEY

Video fire smoke detection using motion and color features [4]:This paper uses color filtering, optical flow for detecting smoke. Color filter find the possible smoke covered regions. Then, optical flow enables detection of motions in the video. Using the magnitude and the directionality of these motions, total outward flux and average upwards motion features are tested in order to confirm the presence of a divergent smoke source and a heat source in that selected region. Extracting these dynamic smoke features produces highly reliable results as it is demonstrated with the test cases.

A probabilistic approach for vision-based fire detection in videos [5]:

Fire detection is an active research topic in computer vision. This approach is usually applied in close-circuit television surveillance scenarios. In contrast, this method can also be applied to automatic video classification for detection of fire in databases. This method analyzes frame to frame changes of specific low level features describing potential fire regions. The behavioral change of each one of features is evaluated and results are combined with Bayes classifier.

SVM based forest fire detection using static and dynamic features [6]:

SVM based approach is proposed for forest fire detection with both static and dynamic features. Based on 3D point cloud of sample fire pixels**,** Gaussian mixture model helps segment some possible flame regions in single image. Then the new specific flame pattern is defined for forest, and three types of fire colors are labeled accordingly. With 11 static features including color distributions, texture parameters and shape roundness, the static SVM classifier is trained and filters the segmented results and the mean square deviation of them are obtained.

Fire detection in video sequences using a generic color model [7]:

It uses YCbCr color space to separate the luminance from chrominance more effectively than RGB color spaces. The performance of proposed algorithm is tested on two sets of images, one of which contain fire, the other containing fire-like regions.

IV.PROPOSED METHODOLOGY:

Optical flow determines motion between two frames or a sequence of frames without any other prior knowledge about the content of those frames. We can associate some kind of velocity with each pixel in the frame or, equivalently, some displacement that represents the distance a pixel has moved between the previous frame and the current frame. Such a construction is usually referred to as a dense optical flow, which associates a velocity with every pixel in an image. The basic block diagram for detection of fire using optical flow method is shown in below figure.

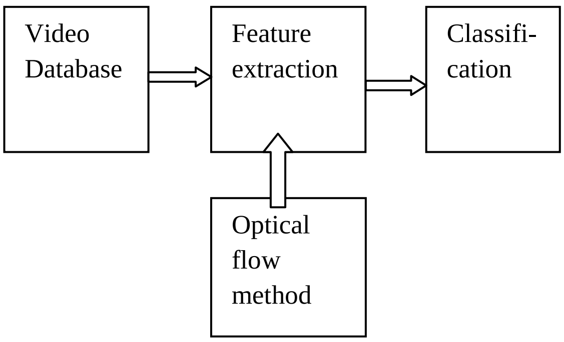

Fig.1.Basic Block Diagram

Classical optical flow methods such as Lucas Kanade and Horn Schunk adopt the features like brightness or intensity constancy and flow smoothness, which are not met by dynamic nature of fire motion. Classical optical flow models only classify the instances of dynamic textures [8], not between presence or absence of an event and they model saturated flames with no dynamic texture [9]. Optical flow fields are created from the video image and some flow features are extracted and classified using supervised machine learning algorithm trained directly on intensity values in the image to ground the truth.

Horn-Schunck method:

This technique was one of the first to make use of the brightness constancy assumption and to derive the basic brightness constancy equations. The solution of these equations devised by Horn and Schunck [10] was by hypothesizing a smoothness constraint on the velocities vx and vy. This constraint was derived by minimizing the regularized Laplacian of the optical flow velocity components:

$$\frac{\partial}{\partial x}\frac{\partial v_x}{\partial x} - \frac{1}{\propto} I_x\left(I_x v_x + I_y v_y + I_t\right) = 0$$

$$\frac{\partial}{\partial y}\frac{\partial v_y}{\partial y} - \frac{1}{\propto} I_x\left(I_x v_x + I_y v_y + I_t\right) = 0$$

Here α is a constant weighting coefficient known as the regularization constant. Larger values of α lead to smoother vectors of motion flow. This is a relatively simple constraint for enforcing smoothness, and its effect is to penalize regions in which the flow is changing in magnitude.

Lucas-Kanade Method:

Using the optical flow equation for a group of adjacent pixels and assuming that all of them have the same velocity, the optical flow computation task is reduced to solving a linear system by Lucas-Kanade method [11][12]. In a non-singular system for two pixels there exists a single solution of the system. However, combining equations for more than two pixels is more effective. In this casethe approximate solution is found using the least square method. The equations are usually weighted. Here the following 2x2 linear system is used:

$$\sum_{x,y} w(x,y) I_x I_y u + \sum_{x,y} w(x,y)\, I_y^2 v = -\sum_{x,y} w(x,y)\, I_y I_t$$

$$\sum_{x,y} w(x,y) I_x I_y v + \sum_{x,y} w(x,y)\, I_x^2 u = -\sum_{x,y} w(x,y)\, I_x I_t$$

Where W(x, y) is the Gaussian window. The Gaussian window may be represented as acomposition of two separable kernels with binomial coefficients.

Optical mass Transport optical flow:

The optical mass transport [13] is also known as Monge-Kantorovich [14] problem. This method is extension of Lucas Kanade and Horn Schunck to estimate dynamic behavior of fire. Optical mass transport feature measures the mean of the transport energy per pixel in the subregion. Fire has a dynamic texture, when burning there is a rapid change occurs in intensity level due to high pressure and heat motion. Characteristics of OMT method: Parameter free, Utilizes grayscale data, symmetrical, optimal mapping, no landmarks required, no local minimizers.

Two features can be extracted from optical mass transport depending on dynamic texture of fire.

1.OMT transport energy with high values of fire spectrum.

2.Matching computed OMT flow field with ideal source flow.

Non-Smooth Data Optical Flow:

This method is applied for saturated flames which are having rigid motion thus disagreeing to OMT's dynamic texture.This value will be high for fire colored objects. NSD flow magnitude can be calculated by taking the mean of half of the square of the norm of NSD flow vectors calculated at each pixel position. NSD flow field mainly applied to boundary motion of the fire when fire reaches its saturation level.

Two features can be extracted from Non-Smooth Data flow method depending on boundary motion of fire.

1.NSD flow magnitude with high values by comparing flow directionality.

2.NSD directional variance.

Neural network:

Neural network is machine learning approach[15]. The network is made up of interconnected group of nodes. Each node process on inputs and provide outputs. The network consists of adaptive weights that are tuned by learning algorithm and are capable of approximating non-linear functions of their inputs. Classification algorithms use the computed features as input and make decision outputs regarding the target's presence. The nodes in neural network are similar to neurons in human brain which can compute values from inputs by feeding information through the network. The feature vector is given as input to the neural network. Neural network involves a series of algorithms that attempt to identify underlying relationships in a set of data by using a process that mimics the way the human brain operates. By identifying the relationship between feature vectors neural network will provide the output as probability of frame being fire.

V.RESULTS AND DISCUSSION:

The proposed work is implemented on MATLAB platform.The below figure shows results that include threshold video of original video, motion vectors and finally detection of fire by bounding boxes which are in green color.

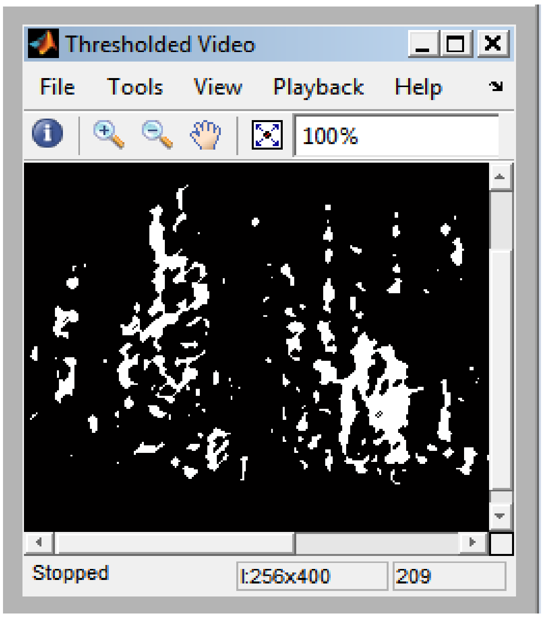

Fig. 2.Thresholding and Region filtering

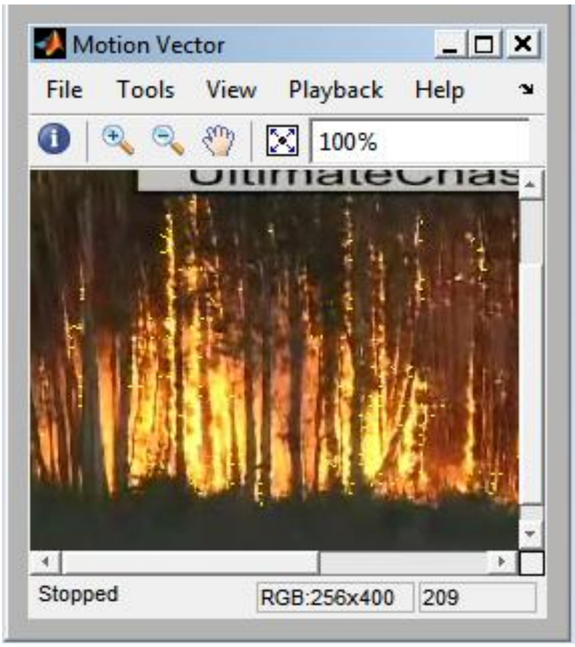

Fig. 3.Motion Vectors

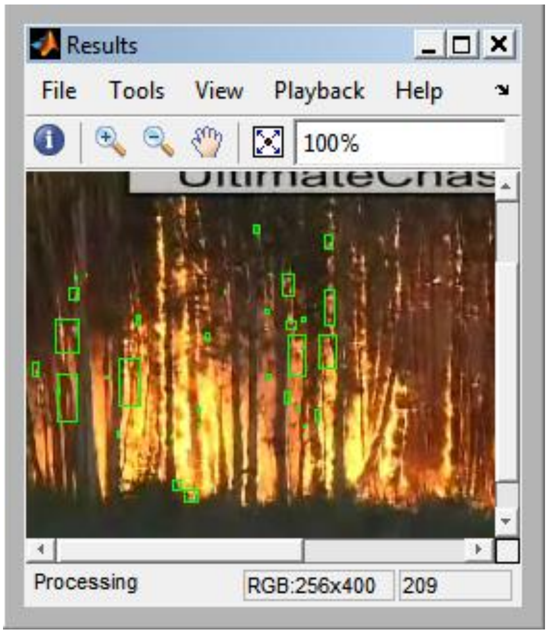

Fig. 4.Detection of fire shown by bounding boxes.

VI.CONCLUSION:

We have presented the methods for fire detection by video tracking using optical flow to provide security for a wide range of applications. The two optical flow fields OMT and NSD have overcome the assumptions of classical optical flow method. These fields define motion features of fire and reject non-fire motion. Neural networks are used for the classification of these features. Little false detection is observed in the presence of noise.

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