Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 3, Issue. 2, February 2014, pg.910 – 916

RESEARCH ARTICLE

Detection of Fire Flow in Videos by SVM Classifier with EM-Segmentation Method

[1]S.Shanthi, [2]J.George Christober

[1]Assistant Professor, CSE, Sri Eshwar College of Engineering, Anna University, Coimbatore

[2]PG Scholar, CSE, Sri Eshwar College of Engineering, Anna University, Coimbatore

[1] shan.sece@gmail.com, [2] iamgeorgepaul@outlook.com

Abstract - In the past decennary computational vision based flame detection has focused significantly with a camera surveillance system omnipresent, whereas many penetrative features such as colour, shape, texture, etc., have been employed in the literature. This paper proposed a motion detection of motion features, the variation of the flow on fire motion in turbulent, fast and rigid motion of the object. The fire motion is not characterized by the classical optical flow methods. Optical mass transport model and Data driven optical flow scheme are the two methods used to detect dynamic texture and saturated flame in the fire detection task combined with EM segmentation image classification process for accuracy of the result. The proposed system we use Support Vector Machine instead of neural network influences.

Index Terms - Fire detection, SVM Classifier, optical flow, EM segmentation

I. INTRODUCTION

Detecting the flame in large area is vital act to prevent the cause of fire damage. The indoor section heat smoking particles are detected by the hardware sensors. The serious issues are to find the flame in an outdoor section. This paper presents the video detection approach where the hardware sensor may fail. In addition to covering a wide viewing range, video cameras capture data from which additional information can be extracted. Surveillance cameras have recently become pervasive.

Reliable vision-based fire detection can feasibly take advantage of the existing infrastructure and significantly contribute to public safety with little additional cost. The video based detection having three steps.

- Preprocessing
- Feature Extraction
- Classification Algorithm

In the first step preprocessing is focused on the hardware devices to do the preliminary operations. The second step Feature extraction having to extracting the variable features and eliminate the unwanted areas and classification algorithm is used to decision regarding process such as Support Vector Machine (SVM) classifier, Support Vector Machine also supports vector networks with associated learning algorithms that analyze data and recognize pattern. Optical mass transport and non-smooth data flow model designed for detecting with and without the dynamic texture of flames, we added the EM segmentation that uses the EM algorithm to estimate the parameters of pixel color and texture features.

II. OBJECTIVE OF THE WORK

The objective of this project is to determine fire detection task can be used in various fields to further reduce the threat of loss of life in residential fires. Early detection at flame ignition can improve the project tasks are as follows:

- Investigate various suitable detection technologies and methods to allow earlier detection of optical flow of flaming fires.
- Investigate the optical flow detection technologies like OMT and NSD optical flow detection method for fire detection can be used to detect the motion fire.
- In the optical flow method is analyzed and combining EM-segmentation method to occur more robustness and the features will be extracted and elimination of unwanted pixels to classify the flow area.
- The SVM classifier to recognize the image pattern and image classification. It appears that unlike most learning techniques, SVM can be trained by database to find the flow area in the images.

III. PAPER CONTRIBUTIONS

A. Preprocessing

Colour transformation is involved in the preprocessing. Read the Input Video and randomly selecting any one of the frame in that video and it will be converting that frame in to grayscale images in the inbuilt process of the module and the feature processing with segmentation and classification is continued to the next modules.

B. Feature Extraction

A naive approach to vision-based detection is to use a supervised machine learning algorithm trained directly on intensity values in the image. This approach will undoubtedly underperform, because the classification complexity increases exponentially with the dimensionality of the problem, in which this case is equal to the number of pixels. Further, the computational cost and the amount of training data required become prohibitively large. Instead, feature extraction is employed by incorporating prior information (known physical properties of the problem or human intuition) for the purpose of reducing the problem dimensionality.

1) Optical Flow

Optical Flow estimation is the process of establishing a common geometric frame of reference from two or more data sets from the same or different imaging modalities taken at different times**.**

2) OMT Transport Energy

An optical flow estimation modeling fire as a dynamic texture, the optimal mass transport (OMT) optical flow. The optical flow problem is posed as a generalized mass representing image intensity transport problem, where the data term enforces mass conservation. This feature measures the mean OMT transport energy per pixel in a sub-region we believe that the proposed OMT optical flow is novel for flame detection because of its regularization and numerical solution. For example, enforces smoothness on the curl and divergence of the flow field, whereas our regularization originates from the optimal mass transport problem which seeks to minimize transport energy. We believe that this choice makes physical sense, since brightness conservation may be naturally regarded as mass conservation.

3) NSD Flow Magnitude

The NSD is explicitly chosen to be non-smooth, since saturated fire blobs are expected to have non-smooth boundary motion. The norm of the flow vector regularizes the flow magnitude, but does not enforce smoothness. This choice, therefore, 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 expected to perform well for standard optical flow applications, where flow smoothness plays an important role, it proves that useful for detecting saturated fire in the regularization term of the NSD optical flow energy.

4) Pre-Selection of Essential Pixels

Static or almost static image regions should be excluded from consideration because of our aim is to characterize the type of motion object is undergoing and they interfere with the motion statistics. For example, the average flow magnitude of a moving object should not depend on the size of the static background, which would be the case if the average was computed over the entire image instead of just the moving region. The set of essential pixels, which are pixels in motion, will be defined as follows. Consider a frame or a sub region of that frame. Then, the set of essential pixels is chosen such that a sufficiently large number of pixels are retained. In case of extreme outliers, the parameter can be adjusted adaptively. In addition, reliability measures could be employed to suppress the pixels with low motion information. Some of the operations of feature extraction will be performed on this subset of "sufficiently moving" pixels.

5) Feature Selection

A list of optical flow features is introduced, which is complete, in that it considers all possible first-order distortions of a pixel. Those distortions are then averaged within a spatiotemporal block to yield the probability of a characteristic direction or of a characteristic magnitude. Reference also mentions that the highest discriminating power comes from the characteristic direction and magnitude of the flow vector itself, not considering distortions. Given the flow vectors, these features share the general idea to use "characteristic" motion magnitude and direction, yet are not the same. In particular, our magnitude features f1 and f2 measures the mean magnitude is opposed to relative homogeneity of the magnitudes within a block, in Our choice is straightforward for fire detection considering the color transformation, thus biasing the detector to fire-like colored moving objects. The other two features f3 and f4 analyze motion directionality. The OMT feature f3 takes into account spatial structure of the flow vectors, a strategy not considered, where all vectors are averaged regardless of their location. Moreover, whereas identifies the presence of one characteristic direction, feature f4 is more general in that it can detect multiple characteristic directions.

6) Combining EM Segmentation

We use the Expectation-Maximization (EM) algorithm to estimate the parameters of this model; the resulting pixel-cluster memberships provide a segmentation of the image. After the image is segmented into regions, a description of each region's color and texture characteristics is produced. The Expectation-Maximization algorithm (EM) is used for many estimation problems in statistics. Here we give a short tutorial on how to program a segmentation algorithm using EM. Those who have interested in the theory or in more advanced versions of the algorithm may consult the references at the end. Suppose we given a set of data points that were generated by multiple processes, for example two lines. We need to estimate two things: (1) the parameters (slope and intercept) of the two lines and (2) the assignment of each data point to the process that generated it. The intuition behind EM is that each of these steps is easy assuming the other one is solved. That is, assuming we know the assignment of each data point, then we can estimate the parameters of each line, by taking into consideration only those points assigned to it.

C. Classification Using SVM

Support Vector Machine (SVM) classifier algorithm to detect the features of fire region. SVM in one of the well-known method for pattern classification and image classification. It is designed to separate the set of training images into two different classes, dimensional feature space, and the class label, SVM builds the optimal separating hyper planes based on a kernel function. All images of which feature vector lies on one side of the hyper plane.

Support vector machine (SVM) is a set of related supervised learning methods that analyze the data and recognize the patterns, thus it is employed in our method for features based classification. The open source package (LIBSVM) is used to construct a two-class SVM classifier. To train the SVM, the static features are computed and collected from sample images with real fire or fire like objects. With the help of these features and radial basis function kernel, we can obtain the main parameters for SVM. Therefore, the segmented candidate fire regions are further checked by the trained SVM classifier, and the false regions can be deleted. Of course, static features can help filter the candidate regions segmented from one single image.

IV. IMPLEMENTATION AND RESULTS

In the classical optical flow methods, optical mass transport model and data driven optical flow scheme are the two methods used to detect dynamic texture and saturated flame in the fire detection task combined with EM segmentation image classification process for accuracy of the result. The proposed system using the Support Vector Machine instead of neural network influences**.**

The video based detection having three steps.

- Preprocessing
- Feature Extraction
- Classification Algorithm.

In the first step preprocessing is focused on the hardware devices to do the preliminary operations, Feature extraction having to extracting the variable features and eliminate the unwanted areas and Classification algorithm is used to decision regarding process such as Support Vector Machine (SVM) classifier. In the optical mass transport and non-smooth data flow model designed for detecting with and without the dynamic texture of flames then we added the EM segmentation uses the EM algorithm to estimate the parameters of a mixture of Gaussians model of the joint distribution of pixel color and texture features.

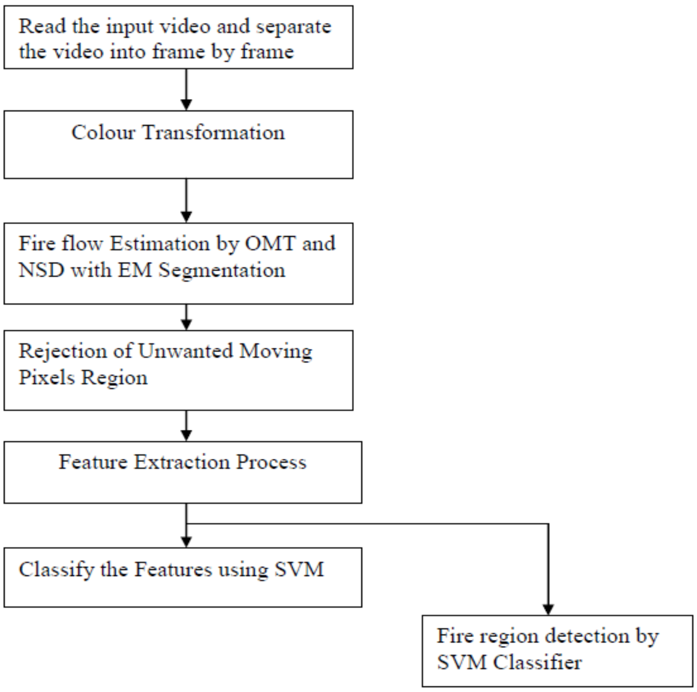
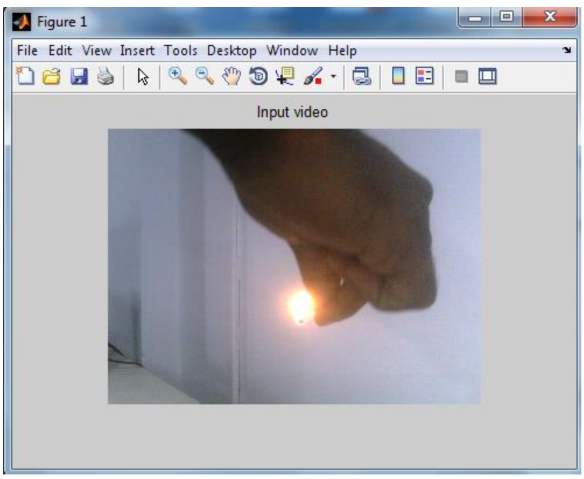


Fig 1. Implementation process flow

RESULTS



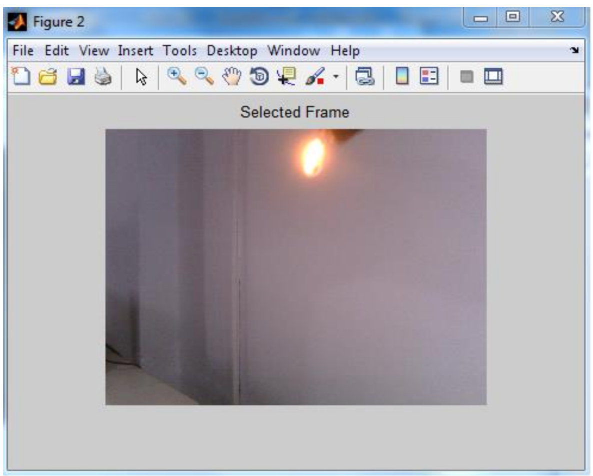


Fig 2. Input Video

Fig 3. Selected frame in the Video

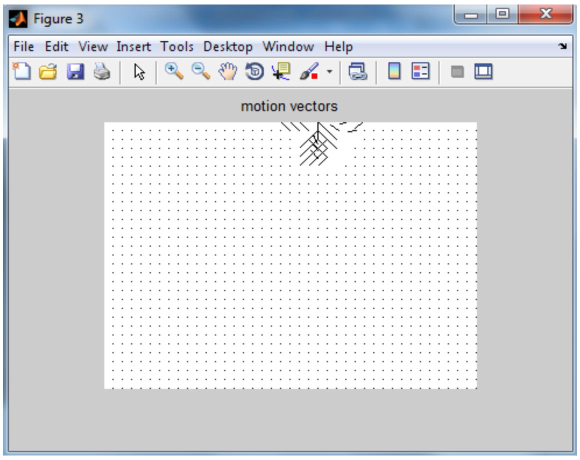


Fig 4. Showing Motion Vector of the Frame

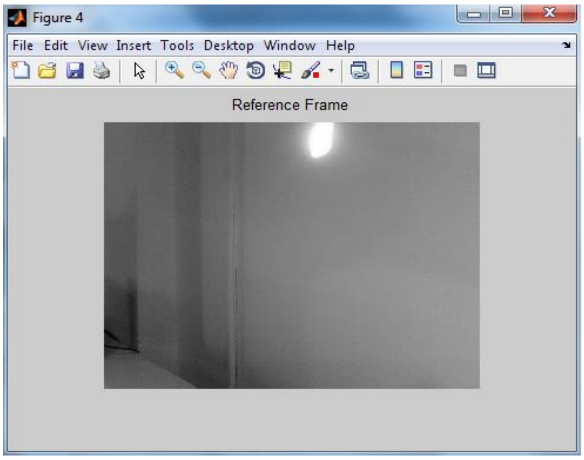


Fig 5. Reference frame of The Color Transformation

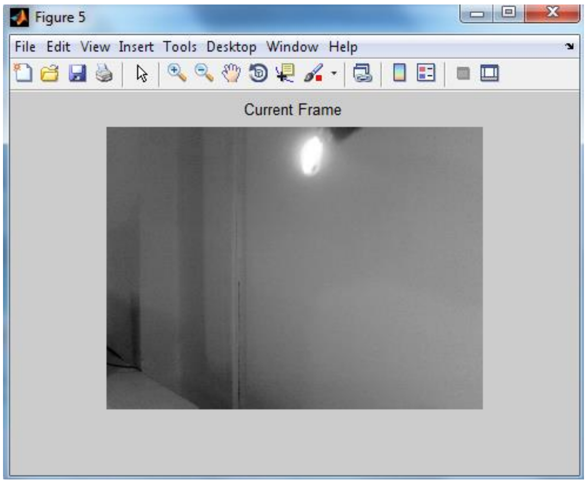


Fig 6. Current frame of the Transformation

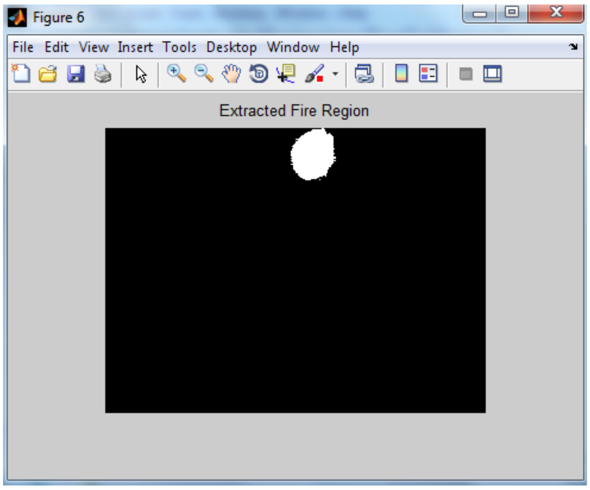


Fig 6. Final Extracted Fire Region of the Frame

V. PERFORMANCE ANALYSIS

A. *SVM Classifier*

SVM for pattern recognition and classification is actually surged in the late 1990s in remote sensing; SVM was primarily used for the hyper spectral image classification and object detection; although researchers have recently expanding its application for multispectral remote sensing data. They provided a detailed introduction of SVM to image classification. The primary advantage of SVM was good generalization capability with limited training samples. The authors acknowledged SVM's limitations in parameter selection and computational requirements. However, SVM provided superior performance compared to most other image classification algorithms for both real-world image data and simulated experiments. The image classification data, they performed a detailed comparison of SVM, and a neural network. These results indicated that SVM substantially good performance compared to the other classifier.

B. *Neural Network*

Neural network classification algorithms have long been used for image classification. Many of them suggested that these types of models are superior to traditional statistical classification approaches, because they do not make assumptions about the nature of data distribution, and the function is simply learned from training samples. Several neural network models have been increasingly used due to their stability and computational performance. For instance they found an increase of 7.0% in overall accuracy compared to a maximum likelihood classification.

The same ARTMAP algorithm was also used by other researchers for time-series NDVI image classification at regional and global scales. The results from ARTMAP algorithm were consistently superior to those obtained from a maximum likelihood classification. It employed the Self-Organizing Map (SOM) neural network technique to classify the Enhanced Vegetation Index (EVI) data. Superior classification results were found compared with those obtained using maximum likelihood classification method. It characterized specific crop types with a Multi-Layer Perception (MLP) neural network model. The principal challenges associated with MLP implementation was the adjustment of network parameters.

VI.CONCLUSTION

The two estimators are used to detect the fire flow and it may having chance of false detection hence, we combine the EM (expectation-Maximization) algorithm with the optimal flow estimators for better results Two novel optical flow estimators, OMT and NSD with the combination of EM Segmentation to overcome insufficiencies of false detection when applied to fire content. The obtained motion fields provide useful space on which to define motion features. These features reliably detect fire and reject non-fire motion, as demonstrated on a large dataset of real videos. Few false detections are observed in the presence of significant noise, partial occlusions, and rapid angle change. In an experiment using fire simulations, the discriminatory power of the selected features is demonstrated to separate fire motion from rigid motion. Future work includes the development of optical flow estimators with improved robustness to noise that take into account more than two frames at a time. The Support Vector Machine classifier (SVM) used for the image classification process by segmenting the optimal clusters on the images .SVM training seem to be more robustness compared with the Artificial Neural Network (ANN).The controlled nature of this experiment allows for the quantitative evaluation of parameter changes. Key results are the need for a minimum spatial resolution, robustness to changes in the frame rate, and maximum allowable bounds on the additive noise level.

REFERENCES

[1]. Aristeidis Diplaros, Nikos Vlassis and Theo Crevers (2007), “A Spatially Contrained Generative Model and an EM algorithm for image Segmentation” IEEE Transaction on neural network, Vol 18, No 3.

[2]. Berwick .R “An idiot`s guide to Support Vector Machine”.

[3]. Chad Carson, Serge Belongie, Hayit Greenspan and Jitendra Malik (2002), “Blobworld:Image Segmentation using Expectation-Maximization and its application toimage querying” IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol 24, No 8,August 2002.

[4]. DongKeun Kim and Yuan-Fang Wang (2009), “Smoke Detection in Video”, World Congress on Computer Science and Information Engineering, Division of Computer Science and Engineering, Kongju National University, 330-717,Korea.

[5]. Jong-Kae Fwu and Petar M.djuric (1997), “EM Algorithm for Image Segmentation initialized by a Tree Structure Scheme”, IEEE Transaction on Image Processing, Vol 6, No 2.

[6]. Le Hoang Thai, Tran Son Hai, Nguyen Thanh Thuy (2012), “Image Classification using Support Vector Machine and Artificial Neural Network”, Published online on www.mecs.com.

[7]. Mengxin Li, Weijing Xu, Kexu,Jingjing Fan and Dingding hou (2013), “Review of fire detection technologies based on Video image”, Journal of Theoretical and Applied Information Technology, Vol 49, No 2.

[8]. Martin Muller, Peter Karasev, Iwan Kolesov and Allen Tennenbaum (2013), “Optical Flow Estimation for Flame Detection in videos”, IEEE Transaction on Image Processing, Vol 22, No 7.

[9]. Yair Weiss “Motion Segmentation using EM- A Short Tutorial” (2013), MIT E10-120, Cambridge,USA.

[10]. Yang Shao, Ross Lunetta.S (2012), “Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification” using limited training data points.

Authors Bibliography

S. Shanthi born in Coimbatore, Tamilnadu, India in 1982. She received B.E degree in Computer science and Engineering from Bharathiar University, Coimbatore & M.E degree in Computer Science and Engineering from Anna University, Chennai. She has published papers in International Journal and Conferences. She is a member of an ISTE. She is an Assistant Professor in Department of Computer Science and Engineering at Sri Eshwar College of Engineering, Coimbatore. Her research interests include Data Mining, Image Processing and Symbolic Data Analysis.

J. George Christober born in Tirunelveli, Tamilnadu, India in 1991. He received B.Tech Degree in Information Technology from Anna University, Coimbatore, India. He is pursuing M.E Degree in Computer science and Engineering in Sri Eshwar College of Engineering, Anna University, Coimbatore, Tamilnadu, India. He is a member of an IEEE Association. His research interests include, Image Processing, Network Security and Web Technology.

