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Vision Based Wildfire Detection Using Bayesian Decision Fusion Framework

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Abstract: Computational vision-based fire and flame detection has drawn significant attention in the past decade with camera surveillance systems becoming ubiquitous. Several signal and image processing methods are developed for the detection of fire, flames and smoke in large and open spaces with a range of up to 30 meters to the surveillance camera in visible-range video. This paper proposes a new approach to vision-based wildfire smoke detection by using a compound algorithm and a decision fusion framework with Bayesian classifier as classification tool. The compound algorithm is a combination of several sub-algorithms, the fusion network is to fuse the outputs obtained by each of these sub-algorithms and finally a Bayesian classifier is used for distinguishing fire regions from non-fire regions. This technique is to improve the accuracy of wildfire smoke detection in videos and to reduce the false alarm rate to a great extent.

Keywords: Computer vision, Bayesian decision fusion, feature extraction, fire detection, generic colour model, image processing.

I. INTRODUCTION

Surveillance cameras have become an important aspect in security and have become a necessity to keep proper check. As the number of surveillance cameras being installed in various fields increased, vision based object detection has become vital worldwide. In computer vision, object detection is the task of finding a given object in an image or video sequence. Several signal and image processing techniques are developed for the detection of different objects from images and video sequences. Detection of fire, flame and smoke is a subfield of vision based object detection and is potentially a useful technique in the implementation of both indoor and outdoor fire alerts. It offers advantages over the traditional methods.

Since fire is a complex but unusual visual phenomenon, unlike normal objects, it has dynamic texture. Due to its frequent size and shape alterations, computational vision-based fire and flame detection algorithms are upon multi-feature-based approaches. The hope and the goal of such algorithms is to find a combination of features whose mutual occurrence leaves fire as their only combined possible cause [1]. Colour, motion, shape, growth, flickering, and smoke behaviour etc. are some of the low level distinctive features of fire regions. Along with these distinctive features, spatial, spectral and temporal features are also used for distinguishing fire regions artificially.

II. RELATED WORKS

W. Phillips, M. Shah, and N. Lobo. [2] proposed a system that uses motion and colour information computed from video sequences to locate fire. First of all a Gaussian-smoothed colour histogram is created and then uses an approach based on this histogram for the detection of fire-coloured pixels. Then, temporal variation of pixels is calculated and by using these calculations the algorithm determines which of these pixels actually fire pixels are. Next, using an erode operation, some spurious fire pixels are automatically removed and using region growing method, some missing fire pixels are found. The technique detects fire reliably under normal conditions. Lack of hardware implementation is a disadvantage. So the algorithm can only be used as part of a robust, well performing, real-time system. High false alarm rate is another disadvantage.

A technique based on Markov models was presented by Toreyin, B.U. et. al. in [3] to detect flames in video. In this

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technique, Markov models are generated to represent the flame and flame coloured ordinary moving objects. Then these models are used to distinguish flame motion from motion of flame coloured moving objects. Spatial colour variations in fire and flame are also evaluated by the same Markov models, as well. Final decision is made by combining these clues. Advantages of hidden Markov models based flame detection are its' robustness and computational efficiency to detect flames in colour video. False alarms due to ordinary motion of flame coloured moving objects are greatly reduced. It has got some disadvantages too. Since the spreading characteristics of flame depend on the strength of the wind, it is impossible to use the same location within a fixed time to model the periodic behaviour of flame boundaries.

Luis Merino et. al. [4] presents a framework for cooperative fire detection by means of a fleet of heterogeneous UAVs. Cameras and other types of fire sensors are incorporated into UAVs. Cameras capture visual images and sensors sense infrared. Computer vision techniques are used to detect and localize fires from these information. The key idea behind the algorithm is that visual colour images of fire have high absolute values in the red component of the RGB coordinates and that the ratio between the red component and the blue and green components. The algorithm uses UV radiation characteristic of fire also. It uses a cooperative state estimation procedure, which estimates the position of the fire and the nature of the fire. Data association is a key problem. Here a simple nearest neighbour strategy is considered. However, in complex scenario, this can lead to bad association. For this kind of sensor, a grid-based localization technique is more suitable for fire localization.

An algorithm which is based on the temporal variation of fire intensity captured by a visual image sensor was proposed by G. Marbach, M. Loepfe, and T. Brupbacher in [5]. Analysis of the full image sequences helps to select a candidate flame region. Characteristic features extraction is done from the candidate flame region and combined to determine the presence of fire or non-fire patterns. If the fire pattern exists over a period of time, fire alarm is triggered. The ''YUV'' representation of the video data is assumed here. Chrominance and luminance are computed. The time derivative of the luminance is zero for the stationary scene regions, and is a non-zero value for moving objects. Six characteristic features are extracted: Luminance, frequency, amplitude, number of active pixels, number of saturated pixels, number of fire-colour pixels. Finally, an "indicator" is used to describe the presence of fire or non-fire.

It has high reliability and a strong robustness towards false alarm in normal environments. The algorithm's reaction time and sensitivity can be adjusted according to the scene complexity and light condition, increasing the flexibility. It has got some disadvantages too. False alarm rate is very high under specific lighting conditions. High luminance or brightness causes image pixels to saturate.

Turgay Celik and Hasan Demirel [6] proposed a rule-based generic colour model for flame pixel classification. The proposed algorithm uses YCbCrcolour space. YCbCrcolour space is more effective to separate the luminance from the chrominance than colour spaces such as RGB or rgb. The key idea is that the fire pixels shows the characteristics that their Y colour value is greater than Cbcolour value and Cr colour value is greater than the Cbcolour value. Even though RGB colour space can be used for pixel classification, it has the disadvantage of illumination dependence. It means that if the illumination of image changes, the fire pixel classification rules cannot perform well. So it is needed to transform RGB colour space to one of the colour spaces where the separation between intensity and chrominance is more discriminate. Since the flame region is predominantly the brightest region in the observed scene, the mean values of the Y, Cb and Cr channels in the overall image contain valuable information.

The number of arithmetic operations for the proposed colour model is linear with image size and algorithm is of low computational complexity. This makes it eligible for the real-time applications. It has got some disadvantages too. Non-fire regions such as car lights, flame reflections, and changing neon lights often exhibit a similar pattern over time; hence, this method cannot provide time analysis of the spread of fire regions in a video sequence.

C. Ho [7] proposed a novel real-time machine video-based flame and smoke detection method. This method can easily be incorporated with a surveillance system for early alerts. In this technique, potential flame and smoke candidate regions are identified by checking weightage of the statistical distribution of the temporal, spectral and spatial probability density is with a fuzzy reasoning system to identify. Smoke and flame colour histogram models are compared in HSI colour space and the spectral probability density is represented. The spatial probability density is represented by computing the flame and smoke turbulent phenomena with the relation of perimeter and area. Flickering area from the video sequences are extracted and alias objects from the flame and smoke region are separated to represent the temporal probability density. Experimental results under a variety of conditions show that the proposed method is capable of detecting flame and smoke reliably. This system requires additional research on fuzzy reasoning in complex moving environments and it requires a complementary tracking algorithm for multiple concurrent fire regions.

A new vision sensor-based fire-detection method was proposed by Byoung Chul Ko et. al. in [8] for an early-warning fire- monitoring system. First, any method for the detection of candidate regions is used for the detection of candidate fire regions. Next, a luminance map is made. The

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key idea behind the generation of this map is that the fire regions generally have a higher luminance contrast than neighbouring regions. This luminance map is used to remove non-fire pixels. Thereafter, the algorithm creates a temporal fire model with wavelet coefficients. This temporal fire model is applied to a two-class support vector machines (SVM) classifier. The kernel used by the classifier is a radial basis function (RBF) kernel. The SVM two-class support vector machine with RBF kernel is then used for the final fire-pixel verification. This approach has robustness to noise and exquisite differences between consecutive frames. This approach has got some disadvantages. Occurrence of frequent false alarms because it uses heuristic features. SVM classifier needs additional computation time depending on feature dimension.

Paulo Vinicius Koerich Borges and EbroulIzquierdo [9] proposed a method that analyses the changes of specific low-level features in the consecutive frames. This analysis helps describing potential fire regions. These low level features are area size, colour, boundary roughness, surface coarseness, and skewness within estimated fire regions. The gradual modification of each one of these features is evaluated, and then combines the results according to the Bayesian classifier for accurate recognition of fire. In addition, the classification results are significantly improved by using a priori knowledge of fire events captured in videos. It has the following advantage. Very fast processing, making the system applicable for real time fire detection as well as video retrieval in news contents. High brightness or luminance causes image pixels to saturate.

Yusuf Hakan Habiboglu et. al. [10] proposed video fire detection system which uses a spatio-temporal covariance matrix of video data. This system divides the video into spatio-temporal blocks and computes covariance features extracted from these blocks to detect fire. Feature vectors are classified using an SVM classifier. The SVM classifier is trained and tested using various video data containing flame and flame coloured objects. The feature vectors takes advantage of both the spatial and the temporal characteristics of flame coloured regions. This method is a computationally efficient method. But if the presence of fire is small and far away from the camera or covered by dense smoke the method might perform poorly. Since the method assumes a stationary camera for background subtraction it cannot correctly classify most of the actual fire regions.

David R. Thompson, William Johnson, and Robert Kremens [11] proposed a method for the detection of wildfire which is used in airborne or orbital image sequences. This technique captures multiple overlapping frames using space vehicles and recognizes stable interest point features in these overlapping frames. It analyses motion between contiguous frames and detects candidate regions over time. To improve sensitivity, the final detection decision joins signal strengths from multiple view. The algorithm is computationally tractable for real-time use on autonomous robotic platforms and spacecraft. It has got higher acquisition rates and potentially improved coverage for remote monitoring. Multiple detections problem is a disadvantage.

Byoung Chul Ko, Sun Jae Ham, and Jae Yeal Nam [12] proposed a novel method using fuzzy finite automata (FFA) for fire-flame detection. FFA is used with probability density functions based on visual features. It provides a systematic approach to handling irregularity in computational systems and it has the ability to handle continuous spaces by combining the capabilities of automata with fuzzy logic. First, using background subtraction moving regions are detected, and then identify the candidate flame regions by applying flame colour models. As the flame regions have a continuous irregular pattern, the variation in intensity, motion orientation and wavelet energy are used to generate probability density functions and it is then applied to the FFA.

This technique is robust for similar cases such as shadows, reflective surrounding areas, rapid changes in colour and motion, and changing neon signs and it performs better if the fire is near to the camera. But if the presence of fire is small and far away from the camera or covered by dense smoke the method might perform poorly.

J. Zhao, Z. Zhang, S. Han, C. Qu, Z. Yuan, and D. Zhang [13] proposed an approach based on SVM. A Gaussian mixture model is built based on 3D point cloud of the collected sample fire pixels and it helps to segment some possible flame regions in an image. Then the newly identified flame pattern is defined for forest, and three types of fire colours are labelled accordingly. With 11 static features and 27 dynamic features, the SVM classifier is trained and filters the segmented results. This trained SVM is used for final decision. It has the following advantage. A total of 27 dynamic features are considered for SVM based final classification, and from every 20 consecutive video frames characteristic features are extracted. Therefore, except for accuracy, the detection algorithm can perform and give alarms in real time. It has got some disadvantages too. This approach has lower accuracy for fire in small regions, and the performance is even worse for small fires covered by smoke.

Y. Habiboglu, O. Gunay, and A. Cetin [14] proposed a video-based fire detection system which uses colour, spatial and temporal information. The video sequence is divided into spatio-temporal blocks by the algorithm extracts covariance-based features from these blocks. By using these extracted features fire is detected. Feature vectors take advantage of both the spatial and the temporal characteristics of flame-coloured regions. A support vector machine (SVM) classifier is trained with some sample features and is used to test the extracted features. This system can be used with non-stationary cameras to some extent because the system does not use a background subtraction method to distinguish

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moving regions from non-moving objects,. Its computational cost in terms of memory and processing power is found to be low. The disadvantage is that if the fire is small and far away from the camera or covered by dense smoke, the method might not perform well.

Martin Mueller, Peter Karasev, Ivan Kolesov and Allen Tannenbaum [15] proposed a set of motion features based on motion estimators for computational vision-based flame detection. In general, fire motion is fast and turbulent. On the other hand, objects other than fire are having structured and rigid motion. The key idea of this algorithm consists of exploiting the difference between these two motions. Classical optical flow methods cannot be used for representing the characteristics of fire motion. So two other optical flow methods are specifically designed for the fire detection task: Fire with dynamic texture is represented using optimal mass transport scheme and saturated flames are represented using a data-driven optical flow scheme. This algorithm extracts characteristic features related to the flow magnitudes and directions from the flow fields. Then these features are used distinguish fire and non-fire motion. The technique requires minimum spatial resolution. It is robust to changes in the frame rate and it has maximum allowable bounds on the additive noise level. It has got some disadvantages too. Little false detection is observed in the presence of significant noise, partial occlusions, and rapid angle change. Osman Gunay et. al. [16] propose an entropy-functional-based online adaptive decision fusion (EADF) framework for image analysis and computer vision applications. In this framework, there is a compound algorithm which consists of several sub-algorithms. Each sub-algorithm has a weight associated with it and the weights are updated online according to the decisions of an oracle. Decision function results obtained by the sub-algorithms are linearly combined with these weights. For the purpose of final classification, an SVM classifier is used. Since it uses online adaptive fusion scheme, the learning duration is decreased. The percentage of error is low for this method. The decision fusion framework proposed by Osman Gunay et. al. in [16] is suitable for problems with concept drift. It has got some disadvantages too. Since the approach uses SVM classifier, learning takes long time. SVM algorithm has several key parameters that need to be set correctly to achieve the best classification results for any given problem. The user may, therefore, have to experiment with a number of different parameter settings in order to achieve a satisfactory result. Computationally expensive, thus runs slow.

III. PROPOSED METHODOLOGY

The Proposed, Vision Based Wildfire Detection Using Bayesian Decision Fusion Framework has the generic architecture as shown in Fig 1.

The proposed system is organized into the following five phases:

•Initialization, Loading input video sequence and initializes system variables.

•Video-Frame Conversion, Converting Video to Frames.

•Individual Decision Making, Obtaining decisions individually by the sub- algorithms on the existence of fire in the input video sequence.

•Decision Fusion and Weight Updating, Combining the decisions obtained by the sub-algorithms and updating the weights associated with each sub- algorithm. This is done by the EADF algorithm.

•Fire Tracking, Showing regions containing smoke in the video sequence on the display.

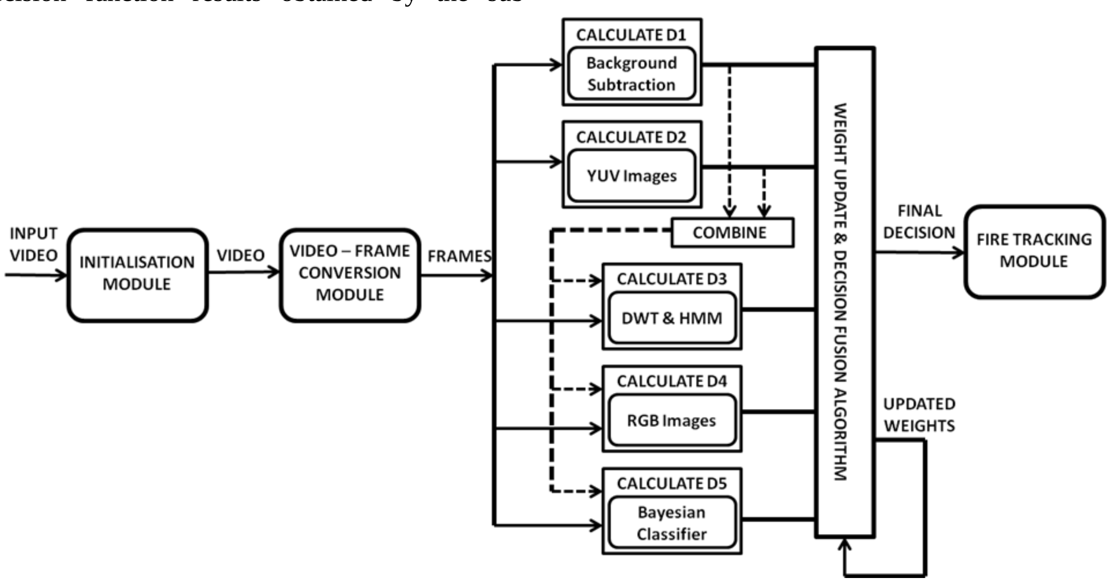

Fig. 1. Architecture - Vision Based Wildfire Detection Using Bayesian Decision Fusion Framework

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An entropy-functional-based online adaptive decision fusion (EADF) framework is proposed in this paper. In this framework, there is a compound algorithm consists of five sub-algorithms and a decision fusion & weight updating algorithm.

First the input video is segmented into frames and these frames are passed through the five sub-algorithms to make individual decisions. The five sub-algorithms used are: 1) slow moving video object detection; 2) smoke-coloured region detection; 3) wavelet-transform-based rising region detection; 4) shadow detection; and 5) covariance matrix based classification using Bayesian classifier.

Each sub-algorithm separately decides on the existence of smoke in the viewing range of the camera. Each sub-algorithm yields its own decision as a real number centred around zero, representing the level of confidence of that particular sub-algorithm. Each sub-algorithm has a weight associated with it and the weights are updated online according to an active fusion method in accordance with the decisions made by a security guard. Hence the weight of a sub-algorithm with poor performance decreases during the training phase and the importance of that sub-algorithm become low in decision making. Decision values obtained by the sub-algorithms are linearly combined with these weights.

In this paper, for the purpose of final classification, we use Bayesian classifier. Various studies in image processing show that Bayesian classifier outperforms all other sophisticated algorithms such as SVM and is a best tool for image classification [17]. A Bayesian classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong independence assumptions. If these independence assumptions actually hold, a Bayesian classifier will converge quicker than other classifiers. Even if the assumption doesn't hold, a Bayesian classifier still performs surprisingly well in practice and it need less training data. Bayesian classifier is fast to classify, fast to train (single scan) and not sensitive to irrelevant features. It can handle real, discrete and streaming data well. Bayesian classifiers have worked quite well in many complex real-world situations. There are strong theoretical reasons for the apparently implausible efficacy of Bayesian classifiers.

IV. IMPLEMENTATION

The implementation of the proposed system is done in MATLAB. The proposed wildfire smoke detection algorithm is developed to recognize the existence of wildfire smoke within the viewing range of the camera monitoring forestal areas. The system consists of five main sub-algorithms: 1) slow moving object detection in video; 2) smoke-coloured region detection; 3) wavelet-transform-based rising region detection; 4) shadow detection; 5) covariance matrix based classification with decision functions D1(x, n), D2(x, n), D3(x, n), D4(x, n) and D5(x, n), respectively, for each pixel point at location x of every incoming image frame at time step n. Computational time and cost efficient sub-algorithms are selected to realize a real-time wildfire smoke detection system working in a standard PC. The outputs of the decision functions are combined in a linear manner, the weights are determined using an entropy-functional-based online adaptive decision fusion (EADF) framework and the final classification is done using a Bayesian classifier.

Decision functions Di, i=1, 2, ..., M of sub-algorithms do not produce binary values 1 (correct) or -1 (false), but they produce real numbers centred around zero for each incoming sample x. If the number is positive (negative), then the individual algorithm decides that there is (not) smoke due to forest fire in the viewing range of the camera. Result values of decision functions express the confidence level of each sub-algorithm. The result value is high means the algorithm is more confident.

A. Slow Moving Object Detection

Using the First Sub-algorithm, the system detects slow moving objects in the video. The key idea is that the system compares each image frame of the input video sequence with the background image extracted from the same video sequence itself. The system performs this action based on background subtraction method.

B. Smoke-Coloured Region Detection

In the Second Sub-algorithm, the system detects smoke coloured regions. For this purpose, the colour content of the image frames is analysed. Smoke due to forest fires is mainly composed of water vapour, carbon dioxide, carbon monoxide, hydrocarbons, particulate matter and other organic chemicals, trace minerals, nitrogen oxides and some other compounds [18]. The greyish colour of the rising plume is primarily due to water vapour and carbon particles in the output re composition. Such regions can be identified by setting thresholds in the YUV colour space. So, the frames are converted into YUV colour space and analyse the colour content to find smoke coloured regions.

C. Wavelet Transform Based Rising Region Detection

Since wildfire smoke regions tend to rise up into the sky at the early stages of the fire, the Third Sub-algorithm tries to detect the rising regions in the video. This characteristic behaviour of smoke plumes is modelled with three-state Hidden Markov Models (HMM). Temporal variation in row number of the upper-most pixel belonging to a slow moving region is used as a one dimensional feature signal, and fed to the Markov models. Transition probabilities of these models are estimated offline from actual wildfires and test fires, and clouds.

D. Shadow Detection

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The system uses the Fourth Sub-algorithm to detect shadows in the input video. Shadows of slow moving clouds are major source of false alarms for video based wildfire detection systems. In this sub-algorithm, average RGB values are calculated for slow moving regions both in the current and the background images. The key idea is that in shadow regions, the angle between the average colour vectors calculated for slow moving regions both in the current and the background images should be small and the magnitude of the vector in the current image should be smaller than that of the vector in the background image. This is because shadow regions retain the colour and the underlying texture to some extent. This sub-algorithm processes image frames in RGB colour space.

E. Covariance Matrix Based Classification

The Fifth Sub-algorithm is a covariance matrix based classification. This sub-algorithm deals with the classification of the smoke-coloured moving regions. In this, we obtain a covariance matrix for each frame by extracting appropriate features. Feature vectors and their extraction are important in this sub-algorithm as it is an essential part of most image processing applications. First, we obtain covariance matrices from extracted features and a Bayesian classifier is trained with these region covariance feature vectors of smoke regions in the training database. To train the Bayesian classifier a number of positive and negative images were used. Positive images are those images having actual smoke and negative images are that do not have smoke in it. For the purpose of performance comparison, we train an SVM classifier too with these covariance matrices. In the testing phase, the proposed EADF Based Wildfire Detection Scheme is evaluated for both Bayesian classifier and SVM as classification tools and the performance of both the systems are compared.

F. Decision Fusion

As pointed out earlier, the decision results of five sub-algorithms D1, D2, D3, D4, and D5 are linearly combined to reach a final decision on a given pixel, whether it is a smoke region pixel or not. The detected pixels then undergo some morphological operations to mark the smoke regions. The number of connected smoke pixels should be larger than a threshold to issue an alarm for the region. If a false alarm is issued during the training phase, the oracle or the security guard gives feedback to the algorithm by declaring a no-smoke decision value for the false-alarm region. Initially, uniform weights are assigned to each sub-algorithm. The decision functions are combined in a linear manner, and the weights are determined using an entropy-functional-based online adaptive decision fusion (EADF) framework.

V. EXPERIMENTAL RESULTS

The proposed system is implemented on a PC with an Intel Core i3 CPU 2.4-GHz processor and tested with forest surveillance recordings captured from cameras mounted on top of forest watch towers. The proposed EADF Based Wildfire Detection scheme is implemented with Bayesian classifier as classification tool. For the purpose of performance comparison, the system is implemented with Support Vector Machine as classification tool too. So, the performance of the proposed EADF Based Wildfire Detection Scheme is evaluated for both Bayesian classifier and SVM as classification tools and the performance of both the systems are compared.

The system is provided with a dataset consisting of about 10 avi files. The size of the videos ranges from 5 MB to 50 MB. The duration of these videos is about 5 secs to 30 secs. The dataset is populated with clips containing forest fire smoke. The Table I and Table II summarize the detection rate of the systems implemented with Bayesian classifier and SVM when tested with a sample dataset having 316 frames. The number of positive images that have actual smoke is 284, and the rest are negative images that do not have smoke.
By analysing the confusion matrices obtained experimentally, for the EADF based wildfire smoke detection system implemented with Bayesian classifier, the success rate is 99.3% for the positive images and 100% for the negative images.

TABLE I
BAYESIAN – CONFUSION MATRIX

		Predicted Labels	
		Not Smoke	**Smoke**
Actual Labels	**Not Smoke**	32	2
	Smoke	0	282

On the other hand, for the system implemented with SVM classifier, the success rate is 96.4% for the positive images and 96.8% for the negative images.

TABLE III
SVM – CONFUSION MATRIX

		Predicted Labels	
		Not Smoke	**Smoke**
Actual Labels	**Not Smoke**	31	12
	Smoke	0	272

In Table III, three video sequences that contain wildfire smoke are tested in terms of true detection rates, which are defined as the number of correctly classified frames containing smoke divided by the total number of frames that contain smoke. The comparison of performance is carried

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out under two schemes, i.e, systems implemented with Bayesian classifier as well as SVM.

TABLE IIIII
COMPARISON IN TERMS OF TRUE DETECTION RATES IN VIDEO CLIPS THAT CONTAIN WILDFIRE SMOKE

Video	Frames	Using Bayesian Classifier	Using SVM Classifier
V1	316	99.3%	95.7%
V2	239	99.0%	94.2%
V3	279	99.2%	95.1%

For the wildfire detection problem, another important comparison criterion is false- negative (miss) detection rate, which is defined as the number of incorrectly classified frames containing smoke divided by the total number of frames that contain smoke. In Table IV, the video sequences that contain wildfire smoke are tested in terms of false-negative (miss) detection rates.

TABLE IVV
COMPARISON IN TERMS OF FALSE NEGATIVE DETECTION RATES IN VIDEO CLIPS THAT CONTAIN WILDFIRE SMOKE

Video	Frames	Using Bayesian Classifier	Using SVM Classifier
V1	316	0.00%	3.12%
V2	239	3.33%	6.70%
V3	279	2.00%	4.20%

Based on the above results and evaluations, it is found evidently that the proposed Entropy-functional-based online Adaptive Decision Fusion based Wildfire Smoke Detection System implemented with Bayesian classifier as classification tool is better than the same implemented with SVM as classification tool.

VI. CONCLUSION

Computational vision-based fire detection is the task of finding the presence of fire regions in an image or video sequence. It has drawn significant attention in the past decade with camera surveillance systems. Various schemes for computational vision-based wildfire smoke detection had been discussed in this paper. Most of these algorithms use spectral, spatial, temporal and other low level features of fire for distinguishing it from other objects in video sequences.
EADF framework is useful to fuse a set of decisions made by several sub-algorithms and hence makes a combined decision. Bayesian classifier outperforms all other sophisticated algorithms and hence it can be used for the final classification in EADF frameworks. With this, detection of wildfire smoke regions in video sequences can be made easier and false alarm rates can be reduced to a great extent.

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