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Video-based Smoke Detection Algorithms: A Chronological Survey

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Abstract

Over the past decade, several vision-based algorithms proposed in literature have resulted into development of a large number of techniques for detection of smoke and fire from video images. Video-based smoke detection approaches are becoming practical alternatives to the conventional fire detection methods due to their numerous advantages such as early fire detection, fast response, non-contact, absence of spatial limits, ability to provide live video that conveys fire progress information, and capability to provide forensic evidence for fire investigations. This paper provides a chronological survey of different video-based smoke detection methods that are available in literatures from 1998 to 2014.Though the paper is not aimed at performing comparative analysis of the surveyed methods, perceived strengths and weakness of the different methods are identified as this will be useful for future research in video-based smoke or fire detection.

Keywords: Early fire detection, video-based smoke detection, algorithms, computer vision, image processing.

1. Introduction

Video-based Fire Detection (VFD) techniques detect fire by recognizing either smoke or flame anywhere within the field of view of the camera at a distance by using numerical analysis to model the monitored area. VFD techniques are becoming viable alternatives or complements to the conventional fire detection methods and have shown to be useful in solving several problems associated with conventional fire sensors (Çetin *et al.,* 2013). VFD techniques have numerous advantages such as fast response, indoor and outdoor detection at a distance, non-contact, absence of spatial limits, the ability to provide live video that conveys fire progress information, and capability to provide pre-recorded video clips as forensic evidence for fire investigations.

Currently available VFD algorithms mainly use models that are trained with observable characteristics of flame or smoke. In early studies, flame detection was mainly investigated. Recently, more attention is being focused on smoke detection. The reason for this can be attributed to the fact that smoke is usually generated before flames and can easily be observed from a long distance, it is therefore an important sign for early fire detection (Chen & You, 2013). Also, smoke spreads faster and in most cases will occur much faster in the camera's field of view. Moreover, previous studies have also shown that smoke is the main cause of deaths in residential fire outbreaks (Prerna & Shaikh, 2013). Therefore, detection of smoke is very important for prevention of fire outbreaks; and to protect people against death from suffocation and inhalation of toxic gases. However, most of the computational techniques being developed for detection of smoke are extension of previous studies on fire detection through flame.

Many smoke detection algorithms using video images captured in visible-spectrum have been proposed. These algorithms extract structural and statistical features from visual signatures such as motion, colour, edge, obscurity, geometry, texture and energy of smoke regions. The extracted features are then used as inputs for rule-based, Bayesian, or rule-first-Bayesian-next analysis to detect presence of smoke. Large number of methods also employ infra-red camera to capture image for smoke detection. Since spatial and temporal characteristics of smoke depend on distance between the camera and the smoke source, different algorithms have been generally designed to detect close range and long range smoke plume. Objective comparison of available algorithms may be difficult due to unavailability of benchmark dataset for smoke detection experiments, and many of the methods are targeted at specific environments such as indoor, outdoor or forest-fire detection. Also, a large number of authors do not provide quantitative assessments of their proposed algorithms.

Related studies in this area are reviews presented by Verstockt, Merci, Lambert, Van de Walle & Sette (2009); Mengxin, Weijing, Ke, Jingjing & Dingding (2013); Çetin *et al.* (2013); and Ahmad (2014). Verstockt *et al*. (2009) present a brief overview of frequently referenced papers on video-based fire detection. Commonly referenced papers on flame and smoke detection techniques are also overviewed in the paper presented by

Mengxin *et al*. (2013). Ahmad (2014) provides a review of different techniques employed for forest fire detection. A comprehensive review of video fire detection is presented by Çetin *et al.* (2013). However, in Çetin *et al*. (2013), more attention is specifically given to the review of algorithms employed in their previous research works on video-based fire detection. Thus there is a need for detailed survey of most of the existing methods which will serve as a platform for development of more robust video-based fire and smoke detection systems.

The aim of this paper is to discuss different algorithms that have been found in literatures for video-based smoke detection. While a significant number of reviewed papers present algorithms for flame detection, smoke detection or both, this study is only limited to the algorithms that are specifically designed for smoke detection in video images. Though over 100 papers are surveyed, our discussion is limited to methods that are considered to be significantly different from others. The rest of this paper is organized as follows: Section 2 presents a summary of representatives of algorithms available in literatures in chronological order. Section 3 gives concluding remarks on direction that video-based smoke detection is following.

2. Existing Smoke Detection Algorithms

In this section, chronological overviews of the available papers (from 1998-2014) are presented. For each of the reviewed papers, the underlying algorithms are briefly discussed and the perceived strengths and weaknesses of each of the methods are equally discussed.

In autonomous forest fire detection system presented by Breejen *et al.* (1998), staring black and white video cameras are used to detect forest fire based on the temporal difference of the smoke plume with the natural background. The acquired image is divided into blocks of equal height and width using a binning table. Moving average and moving standard deviation are then obtained for each bin. A moving average is used to follow normal variations in bin intensity due to sun and clouds. A decay filter is used to estimate the moving average of each bin, where the new moving average is the sum of a fraction (**α**) of the old average and another fraction (**1-α**) of the current average. The period of averaging is therefore adjustable by changing these fractions. The variance in the bin intensity is estimated using moving standard deviation. The bin standard deviation is computed as the square root of the difference between the moving square average and the square moving average. Another decay filter is used in estimating the moving standard deviation. For detection, two thresholds (a lower bound and an upper bound) are introduced. The upper bound is set at the moving average plus a constant (**k**) times the moving standard deviation and the lower bound is set at the moving average minus **k** times the moving standard deviation. A bin with an average intensity outside the thresholds is considered to be a smoke candidate. Bins with detections in the last 16 times is clustered, and confirmed as smoke block. Considering the hardware and computational techniques available at that time, the algorithm represents a major work in video-based smoke detection. However, the approach is too basic considering complex interplay of dynamic changes in the background, occlusion, and presence of slowly or repetitively moving objects.

Kopilovic, Vagvolgyi & Sziranyi (2000) exploited non-self-similarity and irregularities in motion of smoke. Two assumptions are made in the approach: motion of smoke tends to be non-self similar (in larger scales its motion is regular in smaller scales it is irregular); and smoke motions are irregular due to its non-rigidity. They computed optical flow field from two adjacent images, and then utilized the entropy of the motion directions distribution as major feature to differentiate smoke motion from non-smoke motion. In accounting for non-self-similarity, a multi-scale optical flow computation is applied with velocity warping. Statistical (Bayesian) decision is then used for final smoke detection. The approach is characterized with high computational cost and high reaction time.

A real-time automatic smoke detection system for forest surveillance stations was implemented by Guillemant & Vicente (2001). Their methods leverage on the assumption that the energy of the velocity distribution of smoke plume is higher than other natural occurrences except for clouds which, on the other hand have lower standard deviation than smoke. Temporal analysis is first performed on image sequences to segment the pixels that exhibit dynamical activity at low frequencies. The cumulative dynamical data is obtained by temporal weighting of the instantaneous low frequency variations. Then, region boundaries are obtained using spatial analysis. For classification purpose, they utilize fractal embedding and linked list chaining to segment smoke regions. The system is reported to have less than 3 minutes as average detection time. This approach is a relatively robust detection algorithm; however, the presence of other moving objects, typical of video-surveillance scenes, is not considered, and the average detection time needs to be reduced to obtain a faster response.

Gomez-Rodriguez, Pascual-Pena, Arrue & Ollero (2002); Gomez-Rodriguez, Arrue & Ollero (2003) used optical flow and wavelet decomposition algorithm for wildfire smoke detection and monitoring. The optical flow algorithm is used for motion detection; while wavelet decomposition is used to solve aperture problem in optical flow. After the smoke is detected and segmented, smoke characteristics such as speed, maximum height, apparent volume, grey level, dispersion and its inclination angle can also be extracted from the image sequences. The algorithm has high computational cost.

Self-similarity property of smoke was exploited by Nobuyuki & Kenji (2004).They used a fractal encoding method to segment smoke regions from grey-scale images. The method attempts to extract smoke regions by discovering the distinguishing features of smoke regions in the code produced by fractal encoding of an image. Some decision rules are then used to find which of the segmented regions actually contain smoke. The method has high computational cost and its performance is not thoroughly tested with a large set of smoke images.

Liu & Ahuja (2004) proposed spectral, spatial and temporal models of fire regions in visual image sequences. The spectral model is represented in terms of the colour probability density of fire pixels. The shape of a fire region is represented in terms of the spatial frequency content of the region contour using its Fourier coefficients. Using auto regressive model of the Fourier coefficient series, the temporal changes in these coefficients are used as the temporal signatures of the fire region. While the results obtained from a large number of scenes show that the method is capable of detecting fire reliably, Fourier Descriptors are however known to be sensitive to noise.

In Töreyin, Dedeoglu & Çetin (2005), a method for close range (<100 meters) smoke detection system is presented. The algorithm consists of five steps: (i) moving pixels or regions in the current frame of a video are determined, (ii) the decrease in high frequency content corresponding to edges in these regions are checked using spatial wavelet transform. If the edges loose their sharpness without vanishing completely (iii) the decrease in U and V channels of them are checked, (iv) flicker analysis is carried out using temporal wavelet transform, and finally (v) shape of the moving region is checked for convexity. The moving regions in the images are found using Collins' background subtraction algorithm with an adaptive threshold. The method relies on the assumption that close range smoke is semi-transparent and because of that the edges of objects in the image frames lose their sharpness when smoke plume covers them. This leads to a decrease in the high frequency content of the image. To detect this behaviour, spatial discrete wavelet transforms of the background image and the current image are calculated and the decrease in the high frequency energy of the scene is monitored using these wavelet images. It is also taken that flame flickering at 10Hz induces a less frequent flicker in the smoke boundaries with a frequency range of 1-3 Hz. This flickering of the smoke is then quantified by applying a temporal wavelet transform to moving pixels. For colour analysis, it is established that independent of the fuel type, smoke naturally decrease the chrominance channels U and V values of pixels. In making final decision, Boundaries of the moving regions that contain candidate smoke pixels are then checked for their convexity along equally spaced vertical and horizontal lines. This relies on the assumption that smoke of an uncontrolled fire expands in time which results in regions with convex boundaries. If all of the above-mentioned criteria are satisfied for a pixel, the moving region comprising that pixel is confirmed as smoke. In Töreyin, Dedeoglu & Çetin (2006), the same background subtraction and spatial wavelet domain analysis methods are used. But this time temporal behaviour of the smoke are modelled using Hidden Markov Models (HMM). The irregular contours of the boundaries of the smoke regions are also represented in wavelet domain to check their high frequency behaviour. The algorithms represent a major step forward in video-based smoke detection. However, they are computationally intensive; produce significant number of false alarms; and lacks flexibility when sudden illumination changes occur in the scene due to the usage of fixed thresholds to analyze the energy of the image and the lack of filtering on the energy decay of smoke regions.

Thou-Ho, Yen-Hui & ShiFeng (2006) proposed a smoke detection algorithm in which moving regions are segmented using a simple frame differencing algorithm after which two decision rules; static and dynamic are applied. The static decision is based on the greyish colour of the smoke, while the dynamic decision rule is based on the spreading characteristics of smoke such as smoke growth-rate and smoke disorder. The greyish colour is described with the intensity component of the HSI colour space. Using statistical analysis, the authors observed that the intensity value of the smoke pixel is in a certain range. Greyish coloured moving objects, such as clouds or shadows may trigger false alarms. Thus, the proposed method may not be a sufficiently robust smoke detection algorithm.

Another algorithm that employs colour analysis and motion detection was proposed by Turgay, Hüseyin & Hasan (2007). The proposed models are based on different colour models for fire and smoke detection. These colour models are obtained by statistical analysis of samples extracted from images. The detection system assumes that at the beginning of a fire, it is expected that the smoke will have colours that range from white-bluish to white, and as the fire progresses, the smoke's colour changes in the range of black-grayish to black. The detection algorithm consists of simple motion detection, thresholding between RGB colour channels and low saturation detection in HSV colour space. Since clouds have greyish colours and the applied simple motion detection will detect clouds as moving objects and, the technique will have high false alarm rates, and it can not be a general approach for detecting smoke of varying colours.

Xiong *et al.* (2007) designed a smoke detection system that uses background subtraction, flicker analysis, contours, and turbulent characteristics of smoke. Adaptive Gaussian mixture models (GMM) are used for background modelling; and pixel values that do not match one of the pixel's background Gaussians are grouped using connected component analysis as moving blobs. The low frequency flickering nature of the smoke is quantified using Mean Crossing Rate (MCR). The moving blobs from the background subtraction module that have sufficient number of flickering pixels inside are used to extract the contours of the candidate regions. These regions are passed through a final classifier that uses features characterizing turbulent behaviour of the smoke. While promising results are obtained, the approach is characterized by relatively high false alarms rate.

Another approach that utilizes background subtraction and flicker analysis was proposed by Xu & Xu (2007). They proposed a fire smoke detection algorithm that uses both static and dynamic features of fire smoke; extracted in four main stages. In the first stage, moving target is detected using background subtraction approach, followed by extraction of the contour of the moving object. After extracting contour of the object, a feature extraction procedure is performed. Mean Crossing Rate (MCR) is adopted to compute temporal periodicity. Also, a measure of the shape complexity given by the ratio between edge length and area is obtained. Features which include growth, disorder, frequent flicker in boundaries, self-similarity feature and local wavelet energy are combined together and normalized to form a joint feature vector. Then, a two layer Back-Propagation (BP) neural network classifier is used for smoke detection. While the system is tested with sufficient number of videos, quantitative measures of number of smoke detected frames and false alarm rates are not presented in the paper.

In the work of Jing, Feng & Weidong (2008), a simple motion detection algorithm is used, after which the irregularity property of smoke is used as feature set. Some other parameters such as foreground area, number of smoke blocks, perimeter of the smoke and area of the smoke are also introduced in order to generate feature vectors. Support Vector Machine (SVM) is then finally used for classification. The method is reported to achieve satisfactory performance however the false alarm rate issue stills needs to be addressed.

Piccinini, Calderara & Cucchiara (2008) proposed a smoke detection system that combines stable background suppression with smoke detection. Statistical and Knowledge-Based Object tracker (which is a temporal median model with knowledge-based update stage) is used for background suppression, while wavelet transform energy analysis and colour analysis are used for smoke detection. To detect motion, the difference between the current image and the background model is obtained and then binarized using two different local and pixel-varying thresholds: a low threshold to filter out the noisy pixels extracted due to small intensity variations; and a high threshold to identify the pixels where a large intensity variation occurs. Objects are then validated using combination of colour shape and gradient information in HSV colour space to remove artifacts and objects due to small background variations. The adopted background model allows a precise segmentation that successfully handles shadows, ghosts, and micro-movement of background objects. The energy variation in wavelet model and a colour model of the smoke are then extracted as features. The decrease of energy ratio in wavelet domain between background and current image is used to detect smoke representing the variations of texture level. A mixture of Gaussians models this texture ratio for temporal evolution. For colour analysis, it is assumed that when smoke starts to expand, scene regions covered by smoke gradually change their colour properties by evolving from being semi-transparent to completely opaque. The proposed method adopts an evaluation based on a blending function derived from computer graphics. A reference colour model in RGB colour space is then chosen to model the smoke colour in the scene; and deviation of the current pixel colour from the model is computed. In order to identify a smoke region in the scene, the block-wise energy ratio and the colour blending features are classified using Bayesian approach whose posterior probability value is thresholded. For each segmented object in the scene the number of candidate blocks intersecting the object's blob is computed; and an object is finally classified as smoke when 70% of its area overlay candidate smoke blocks. Satisfactory results are obtained using the method; however the technique does not cater for smokes that have colours that differ from light-gray.

Yuan (2008) proposed an accumulative motion model based on the integral image by fast estimation of the motion orientation of smoke. The algorithm employs motion detection together with direction of the motion flow and colour information to detect smoke. Moving regions are detected by applying frame differencing to sub-blocked images. The smoke colour is determined using thresholds in RGB colour space. The smoke is assumed to move upwards and the histogram of the accumulated orientations is used to extract the direction of the motion. To compensate for inaccuracy of orientation estimation, the accumulation of the orientation over time is performed. It is reported that the model is able to eliminate the disturbance of artificial lights and non-smoke moving objects. However, the motion estimation algorithm is very slow in the context of smoke detection. Also, the applied chrominance based methods are not reliable due to their dependence on the colour of smoke.

Gubbi, Marusic & Palaniswami (2009) proposed outdoor smoke detection approach based on wavelets and support vector machine (SVM). In the scheme, image frames are divided into small blocks of 32 x 32 pixels and the smoke characterization is carried out using standard pattern recognition approach with preprocessing, feature extraction and classification sub-units with training and testing phases. In the study, discrete cosine transforms (DCT) and wavelet transforms are used to generate features; and the extracted features are separately tested using a linear classifier (K-NN) and non-linear classifier (SVM) to investigate their respective performances. It is found that the combination of wavelets and support vector classifier gives the lowest incidence of false positives, highest sensitivity of 0.9 and specificity of 0.89. After preliminary testing, three-level Daubechies wavelet is finally chosen in the scheme, where the horizontal, vertical and diagonal components at each level are computed. In order to obtain a reduced and better representation from generated features, six derived features: arithmetic mean, geometric mean, standard deviation, skewness, kurtosis and entropy are calculated from the coefficients of the wavelet sub-bands. A total of 60 features for three levels is obtained, and used as the input to a radial basis function–based binary SVM classifier. Though very promising results are obtained, the large dimension of the feature vector might make the method to be too slow for practical smoke detection scheme.

A method that utilizes wavelet features and neural networks was developed by Yu, Zhang, Fang & Wang (2009). The approach uses texture analysis to detect smoke for real-time fire detection. The proposed method consists of three main stages. First, the video frames are divided into number of blocks. Then adaptive Gaussian Mixture Model (GMM) algorithm is then used for background subtraction in order to determine foreground pixels in the blocks. If number of foreground pixels in a block is greater than a certain threshold, the block is considered as a candidate block. Lastly, feature extraction using GLCM is performed for each of the candidate blocks. To determine the characteristic of smoke regions, the features are generated by computing the energy, contrast and homogeneity of the related candidate block. The extracted features are then applied to a BP neural network for classification. Although the authors reported promising results from 2 smoke and 2 non-smoke videos only, the algorithm needs to be tested on a large dataset that have smoke textures of different sizes and varied noise levels. Also, for real-time application, the feature extraction and classification steps need to be well optimized.

Verstockt, Merci, Lambert, Van de Walle & Sette (2009) proposed a chromaticity-based smoke detection algorithm with back-step correction. The proposed smoke detection algorithm consists of five steps: (i) sub-blocking (ii) background subtraction, (iii) energy analysis, (iv) boundary disorder analysis, and (v) clean-up post-processing. In order to overcome instability of standard background estimation methods in smoke motion detection, a more robust background estimation method that can cope with the gradual characteristic of smoke is proposed. A moving (smoke) block is determined by comparing the YUV chrominance values of a given block in the current frame with the values of the corresponding block in the background model. If for more than half of the pixels in the block, the difference of the absolute values of the chrominance values exceeds a pre-defined chrominance threshold, the block is labelled as foreground. Average absolute chrominance value, standard deviation of the spatial luminance difference are also used to prevent labelling of blocks with very low chrominance values as background; while current background block is compared with previous background estimations in back-step correction arrangements to overcome problems of gradually appearing smoke. Foreground blocks are grouped into connected regions, i.e., blobs. For each of the blobs, the algorithm uses energy and boundary disorder analysis to make a final decision as whether the blob in a given frame contains smoke or not. Using the discrete wavelet transform, the energy of the blob intensity values is compared with the energy of the intensity value of the blob region in the background estimated frame and the background buffer. If the blob energy drops and the energy variation exceeds a pre-defined threshold, the blob is labelled as candidate smoke. Then, for each candidate smoke blob, the boundary disorder of the blob is analyzed over time using turbulence metric, which is computed by relating the perimeter of the candidate blob to the square root of the area of this blob. If the boundary variation between the blob, the blob region in the background estimated frame and the buffer exceeds another threshold, the blob is labelled as smoke. The algorithm is shown to work in real-time with reduced false alarms compared to the other methods. However, the use of fixed thresholds renders the algorithm inflexible. Also, smoke localization is not possible with the approach.

An algorithm for long range smoke detection in a wildfire surveillance system was developed by Töreyin & Çetin (2009). The algorithm is an online learning method that employs human judgement (an oracle) to update its decision values. The main detection algorithm consists of four sub-algorithms detecting (i) slow moving objects using adaptive background subtraction, (ii) gray regions using YUC colour space, (iii) rising regions using hidden Markov models (HMM), and (iv) shadows using RGB angle between image and the background. Each algorithm yields a fuzzy decision value as a real number in the range [-1, 1] at every image frame of a video sequence. Decisions from sub-algorithms are combined using the Least Mean Square (LMS) method in the training stage. The error function which is the difference between the overall decision of the main algorithm and the decision of an oracle is minimized using LMS to obtain the correct classification. It is reported that the proposed active learning scheme has relatively lower learning duration when compared with some other methods (Kose *et al.* 2009). The system is reported to produce average of 1 false alarm in 4 hours.

Damir, Darko & Toni (2009) investigated different colour space transformations and feature classifiers that are used in a histogram-based smoke segmentation for a wildfire detection system. One of their goals is the selection of the algorithm-colour space combination for the task of smoke detection. They provide evaluations of histograms in YCrCb, CIELab, HSI, and a derivative of HSI colour spaces. Look up tables (LUT) and two different naive Bayes classifiers with different density estimation are used to classify the histograms. Their results show that the classifier performance is not significantly improved across different colour transformations. Each classifier shows similar performance for each colour space but maximum rates are achieved at different resolutions. The best performances are achieved with HSI and RGB colour spaces when used with the Bayes classifier. The proposed algorithm is claimed to be successfully implemented as one of the smoke detection methods of the Intelligent Forest Fire Monitoring System (iForestFire) that is used to monitor the coastline of the Republic of Croatia.

Qinjuan & Ning (2009) proposed a technique for detecting moving smoke regions in automatic forest fire surveillance. The first part of the algorithm uses finite thresholding processing to each differential frame after multi-frame temporal difference operation to extract the persistent dynamic behaviour of forest smoke from serial forest fire frames. Their algorithm also employs colour and area growth clues for effective discrimination from similar natural phenomena. In the classification stage, they use colour information and growth rate. It is reported that high detection rate is achieved and false alarm rate is confined to 15%. However, usage of colour for classification may make the technique unreliable. The approach is also not robust in environments with other moving objects and noisy image acquisition devices.

Dongil & Byoungmoo (2009) proposed a method for real-time detection of fire and smoke in a tunnel environment. They use motion history images to implement a background subtraction algorithm. Invariant moments are used to separate smoke from ordinary moving objects. Colour and motion information are also used to minimize false detections in tunnels. The method is shown to work successfully in a tunnel environment.

In most VSD algorithms, the camera is supposed to be stationary but there are some studies which try to handle moving camera as well. DongKeun & Yuan-Fang (2009) proposed a block-based three-step smoke detection system. In the first step, decision is made on whether the camera is moving or not. If the camera is moving, the ensuing steps are skipped. Otherwise, the second step is to detect the areas of change in the current input frame against the background image and to locate regions of interest (ROIs) - blobs- using connected component analysis. The block subtraction approach is applied in both the first and second steps. The final step is to determine whether the detected blob indicates smoke using k- temporal colour and shape information extracted from the ROI. The distance of blobs is calculated using two points which have a minimum distance between the two blobs. The merged blobs are represented using a bounding polygon from a convex-hull algorithm; and all small blobs are merged into one big one. The algorithm then extracts features that include area, bounding rectangle, the average and standard deviation of Y-value, and the average and standard deviation of UV-value of the YUV colour channel. Features, which are calculated from **k** previous temporal frames, are kept. A blob is classified as smoke if it changes its shape and area continuously and has similar statistics in the Y-value in all **k** frames. The approach produces some promising results. Only two videos are used in the experiments; the approach therefore needs to be tested on more datasets. Also, performance of the proposed system in real time applications needs to be verified.

Another method for real-time video-based flame and smoke detection was proposed by Ho (2009). Motion history images are used to find the moving pixel positions whose spectral, spatial and temporal characteristics are later analyzed to locate the smoke regions. Spectral probability density of the regions is represented by comparing the flame and smoke colour histogram model which are obtained in HSI colour space. The perimeter and area of the regions are used to represent the spatial probability density of the smoke. The candidate regions are obtained using the spectral and spatial densities in a fuzzy reasoning framework. Level crossing is then used to detect the flickering frequency of the candidate regions, represented as temporal probability density which is used for separation of the flame and smoke region from similar objects. Continuously adaptive mean shift is used to provide the real-time position of the smoke regions as a feedback to the detection algorithm. The algorithm was tested under different conditions and was reported to provide reliable detection performance. Although promising results are presented in the paper, the approach requires additional research on fuzzy reasoning in complex moving environments.

Zhou, Yi & Xiaokang (2010) developed a system for fire and smoke detection using quaternionic wavelet features. In the approach, moving objects are considered as candidate smoke regions when they are characterized by velocity in a positive vertical direction. Also, local spectral, spatial and temporal characteristics of fire regions are obtained using quaternion Gabor wavelets. To reduce false alarms, 1D temporal filter kernel is used to capture random flickering behaviour in the fire regions. Five GLCM-based texture descriptors, Entropy, Contrast, Angular Second Moment, Inverse Difference Moment and Image pixel correlation, together with the mean value of the candidate smoke regions are then used to train a support vector machine (SVM) model. Though computationally intensive, the experimental results under a variety of conditions show that the method has better performance than some of the previous approaches.

The problem of differentiating smoke from non-smoke sources (such as flashlight beams) in the night is addressed by Liu, Yu & Zhang (2010). They introduced an infrared camera to detect the smoke in the night-time. This approach uses an original image gray scale method to extract the smoke. It then uses smoke detection flow diagrams to detect the real smoke. Various studies (Töreyin, 2009; Gunay, Tasdemir, Töreyin & Çetin, 2009; Verstockt *et al.,* 2010) have equally shown that problem of detecting smoke in the night or in poorly lit environments can be tackled by using infrared cameras.

Ma, Wu & Zhu (2010) proposed a method that uses Kalman filter and Gaussian colour model to detect smoke in image sequences. Moving objects are firstly detected using image subtractions from adaptive background of a scene through Kalman filter and MHI (Moving History Image) analysis. Then a Gaussian colour model, trained from samples using offline EM algorithm, is used to detect candidate fire smoke regions. Final smoke confirmation is carried out using temporal analysis of dynamic features of suspected smoke areas where higher frequency energies in wavelet domains and colour blending coefficients are utilized as smoke features. The algorithm has not been tested on large datasets.

Maruta, Kato, Nakamura & Kurokawa (2010) considered that the image information of smoke is a self-affine fractal, and they used extracted local Hurst exponent to analyze the self-similarity of suspect smoke region. Firstly, moving objects are detected from gray scale image sequences, and then noise removal is carried out using image binarization and morphological operation. The smoke feature is extracted using texture analysis. Then, the extracted features are treated as time series data to obtain the final result on smoke detection.

Inspired by the airlight-albedo ambiguity model, Chengjiang *et al.* (2010) introduced transmission as a new essential feature for detecting smoke and also to determine its corresponding thickness distribution. Smoke optical model is firstly built, using airlight-albedo ambiguity model. Then the preliminary smoke transmission using dark channel prior (this is basically colour analysis in RGB colour channels) are estimated and then refined using soft matting algorithm. Finally, transmission is used to detect smoke region by thresholding; and detailed information about the distribution of smoke thickness is obtained through mapping transmissions of the smoke region into a gray image. It is reported that the method is very efficient in detecting heavy or light smoke, and very useful in estimating smoke thickness distribution. However, the method is limited to detecting gray-white smoke; and quantitative information about its performance is not available.

Habiboglu, Gunay & Çetin (2011) developed a video based wildfire detection system that is based on spatio-temporal correlation descriptors. The proposed algorithm consists of three main sub-algorithms: (i) slow moving object detection in video, (ii) smoke-coloured region detection, and (iii) correlation based classification. For moving object detection a Gaussian mixture model (GMM) based background subtraction method is employed. During the few seconds of learning duration, very fast background update is performed; after which the background update is performed very slowly so that small and slow moving objects can be detected. For colour analysis, Smoke coloured regions are identified by using threshold-based approach in YUV colour space. It is taken that luminance value of smoke regions should be high, while the chrominance values should be very low for most smoke sources. Thus, an image pixel is taken to be smoke if its luminance is higher than a threshold; and its chrominance values are lower than another set of experimentally-determined thresholds. For feature extraction, temporally extended and normalized correlation descriptors are proposed. This approach assumes that smoke coloured image regions do not contain strong edges, and they exhibit wide-sense stationarity. Thus, covariance descriptors are used to model spatial characteristics of smoke regions in images. An SVM classifier is finally used for training and testing of the obtained descriptors. The method is computationally efficient; however it may be characterized by poor performance if the smoke is highly dense or it is small and far away from the camera.

A forest smoke detection scheme using spatial-temporal features and a random forest-based pattern classification technique is proposed by JoonYoung, ByoungChul & Jae-Yeal (2011). Firstly, moving regions are detected from difference between two consecutive key frames, whenever the difference is above a certain threshold. After detecting the candidate smoke blocks, the image is scanned to group the blocks into clusters based on block connectivity using morphological closing. The spatial-temporal visual patterns of intensity, wavelet energy and motion orientation are then extracted from 100 consecutive frames to form feature vector. For the energy feature, the average of wavelet energy and skewness of the wavelet energy is computed from candidate smoke blocks using a linear combination of high frequency coefficients after a Daubechies wavelet transform. Also, the motion orientation between the current and previous key frames is estimated based on the assumption that smoke tends to move upward due to heat convection. After estimating the motion for each block, the orientation of the motion is discretized into eight directions, and each discrete direction is coded as 1–8. The final feature vector for each block (whose dimension is 5) is then normalized to unit length using the Gaussian normalisation method. The extracted smoke candidate blocks are then trained using decision trees of random forests. The proposed algorithm is reported to show a better detection performance. However, considering the large number of consecutive video frames required to build a feature vector, the scheme may be too slow for real-time application. Also, the effect of wind on the smoke direction might have been ignored in the algorithm.

Yuan (2011) proposed an effective feature vector by concatenating the histogram sequences of Local Binary Pattern (LBP) and Local Binary Pattern Variance (LBPV) pyramids, and a back propagation neural network was used for smoke detection. Yuan (2012), employed a double mapping framework to extract partition based features of smoke, AdaBoost was employed to enhance the performance of classification. The first mapping is from an original image to block features. A feature vector is presented by concatenating histograms of edge orientation, edge magnitude and Local Binary Pattern (LBP) bit, and densities of edge magnitude, colour intensity and saturation. To obtain shape-invariant features, a detection window is partitioned into a set of small blocks called partitions, and many multi-scale partitions are generated by changing block sizes and partition schemes. The sum of each feature image within each block of each partition is computed to generate block features. Also, the statistical features of the block features, such as, mean, variance, skewness, kurtosis and Hu moments, are computed on all partitions to form a feature pool. AdaBoost is used to select discriminative shape-invariant features from the feature pool. Experiments show that the proposed method has better generalization performance and less insensitivity to geometry transform than conventional methods. The approach adopted is demonstrated to achieve the best performance in regard of state-of-the-arts then.

Leonardo *et al.* (2012) proposed a smoke detection scheme that is designed for MJPEG codec system. The scheme consists of four stages: video frames acquisition stage, DCT inter-transformation based pre-processing stage, smoke region detection stage and region analysis stage. In the video frames acquisition stage, each frame is captured by an IP camera and encoded using standard JPEG codec, in which bi-dimensional DCT is applied to non-overlapped blocks of 8 × 8 pixels of each frame. In the pre-processing stage, the DCT inter-transformation is applied to all DCT blocks of 8 × 8 coefficients of each frame to get DCT blocks of 4 × 4 coefficients without using the inverse DCT (IDCT). In the smoke region detection stage, motion and colour properties of smoke are analyzed to get the smoke region candidates. This stage receives DCT blocks of coefficients previously calculated by the pre-processing stage of each frame, which is made up of three channels: luminance channel (Y) and two chrominance channels (Cb and Cr). The motion property of smoke is analyzed using only the luminance channel Y, and the smoke colour property is analyzed using two chrominance channels Cb and Cr. The candidate regions are processed using morphological operations to eliminate isolated blocks. Using the connected component labelling algorithm, the smoke expansion properties of the candidate regions are analyzed through time to discard non-smoke regions. The algorithm has relatively high false alarm rate when the background and smoke colour is similar; and when the camera is very far from the smoke source.

In Timothy (2012), a multispectral video-based smoke detection is proposed. The study incorporates spectral, temporal and spatial attributes of a smoke plume for early forest fire detection. Multispectral (red, green, blue, mid-wave infrared, and long-wave infrared) image processing techniques are used to segment and identify the presence of a smoke plume within a scene. The temporal and spectral variance of a smoke plume is obtained using Multispectral-Multitemporal Principal Component Analysis (PCA) performed on a sequence of video frames simultaneously. The presence of a plume existing in one of the higher order principal components is determined by the texture of its spatial content. The texture is characterized by statistical descriptors derived from the principal component's joint probability density distribution of intensities occurring within Gray Level Co-Occurrence Matrix (GLCM). It is reported that a smoke plume is readily segmented via PCA; and within these principal components, the smoke's presence is best identified by the correlation texture descriptor since smoke is very spatially correlated when compared to the scene at large. Smoke classification is finally performed using thresholded correlation of the spatial texture of the principal component containing smoke. Neither quantitative nor qualitative assessment of the algorithm's performance is presented.

Chen-Yu, Chin-Teng, Chao-Ting & Miin-Tsair (2012) proposed a smoke-detection approach that utilizes block-based spatial and temporal analyses. A candidate-region extraction step is firstly performed using a combination of temporal difference and GMM background subtraction techniques. Then, the method extracts energy-based and normalized-RGB colour-based features within the spatial, temporal, and spatial-temporal wavelets domains. The three features are combined and fed to a Gaussian kernel-based SVM for classification. To reduce the false alarm rate and maintain a high detection rate with a short reaction time, a temporal-based alarm decision unit (ADU) is introduced. They obtained average detection rate of 83.5 %, false-alarm rate of 0.1% with average reaction time of 1.34 seconds. Their experimental results show that the proposed algorithm can detect smoke with a low false alarm rate and a short reaction time. However, the colour-based features might make performance of the approach to be dependent on the colour of smoke.

Konstantinos, Alexia & Ioannis (2012) proposed an algorithm for accurate smoke localization in space and time under various challenging conditions, such as wind blowing, or other moving objects. Background and foreground separation is firstly carried out using motion information. Histograms of oriented gradients (HOGs) and histograms of oriented optical flow (HOFs) are then constructed to take into account both appearance and motion information. Afterwards, they are averaged over time for temporal smoothing, leading to a spatio-temporal descriptor for each candidate block. Afterwards, a visual vocabulary is built by applying hierarchical k-means clustering on these descriptors, where a fast bag-of-words is developed. Finally, a kernel matrix is created by comparing training data in a pair-wise manner, and an SVM classifier is used to detect frames that contain smoke. In the second stage of the algorithm, spatial localization smoke particles in each frame where smoke is detected is carried out using threshold-based colour analysis in HSV colour space, as well as energy analysis using Sobel edge detection filter. The algorithm was tested on Bilken University and the Visor smoke datasets, where remarkable results were obtained. However, no information is provided about the algorithm reaction time.

Teresa, Vidal & Gabriel (2012) proposed a novel unsupervised smoke classification technique. Single visual features are classified using a model that simultaneously creates a codebook and categorises the smoke using a bag-of-words paradigm based on LDA model. The method does not require segmentation, extraction of ROIs or motion estimation in the image. Instead, visual features (obtained from Scale Invariant Feature Transform -SIFT) are directly classified using a novel object classifier that simultaneously creates a codebook and categorises the smoke using a Bag-of-Words (BoW) paradigm. In the visual BoW model, the codebook generation and the modelling tasks are treated independently. Firstly, the codebook is generated using all the descriptors of the training set and then a model that considers some characteristic in the data is learnt. The two tasks are integrated together. It is reported that the algorithm can simultaneously generate a codebook and categorise a topic using a probabilistic generative model. The proposed integrated approach is fully probabilistic and retrieves the amount of smoke available in a given image. An average classification accuracy of 89.61 was obtained by using the method on two image sequences taken with different visual cameras mounted on a moving platform. The method needs to be tested on large datasets with varying background conditions.

An interesting virtual environment for evaluating smoke detection algorithms was proposed by Ruggero, Angelo, Vincenzo & Fabio (2012). They introduced a virtual environment, based on a cellular model, for the computation of synthetic wildfire smoke sequences. The proposed smoke simulation method is designed to model long-range wildfire smoke clouds, which can be used to train classifiers used by wildfire detection methods. The method is based on a lightweight physics-based model that uses the rules of propagation and collision to recreate the basic principles of advection, diffusion, and buoyancy. External forces, such as wind, are simulated by adding pseudorandom variations in the virtual model. The resulting smoke plume is then merged with a real frame sequence. Finally, adverse environmental conditions, such as low illumination, fog, and acquisition noise, are added to the model. The main parameters used in the simulation to control the strength of the smoke are the extension, density, and speed of the simulated smoke plume. The proposed approach are divided into the following steps: (1) initial plume computation; (2) external forces computation; (3) velocity estimation; (4)

merging with the frame sequence; (5) simulation of adverse conditions. It is reported that accurate results were obtained using the proposed approach, and that the simulated synthetic smoke sequences allows creation of realistic datasets, which can be used to train smoke detection systems and increase their accuracy and adaptability.

Chunyu, Zhibin & Xi (2013) presented real-time video fire flame and smoke detection method based on foreground image accumulation and optical flow technique. The proposed method is divided into four major phases: First, moving pixels and regions are extracted from the image using frame differential approach. Second, static colour models are used to find smoke candidate regions. Third, foreground accumulation images are built for smoke. In the last phase, motion features of smoke are calculated using block-based image processing and optical flow technique. The method assumes that smoke is usually grayish in colour; and that the three components R, G, and B of smoke pixels are more or less equal. Maximum, minimum and average intensity of a given pixel in RGB colour space is then compared against some experimentally determined thresholds. Block–based Pyramid Lucas-Kanade optical flow techniques are used to extract the motion features of smoke. To reduce computation complexity of optical flow calculations, the pixels in the centre of each smoke block are considered as feature points. Finally, a Back-Propagation Neural Network with log-sigmoid transfer function is then used for the smoke feature classification. Undoubtedly, the method will be less computational intensive; however it can not be used in the situations where smoke colour is not greyish.

Leveraging on the remarkable results obtained by researchers in dynamic textures segmentation, Chen & You (2013) proposed feature extraction methods that exploit dynamic characteristics of smoke for video based smoke detection. The proposed algorithm is made up of various block-based processing stages which include candidate smoke blocks detection using motion and colour in RGB colour space; and candidate smoke blocks verification using accumulative motion orientation, Histograms of Equivalent Patterns (HEP)-based spatial texture descriptors, and Space-time Feature Analysis which consists of inter-frame difference and dynamic texture Descriptors on Three Orthogonal Planes. They introduced Edge Orientation Histogram (EOH) in three orthogonal planes; carried out extensive comparative studies on major spatial and dynamic texture descriptors. The performance of the proposed features is evaluated using SVM classifier. At the final stage of the algorithm, Smoke History Image (SHI) is introduced to compute a confidence value from the current and historical classification results of candidate smoke blocks to reduce false alarm. Experimental results show improved detection accuracy, and false alarm resistance are achieved compared with the state-of-the-art technologies.

Problem of video smoke detection during night-time is uniquely addressed in a paper presented by Chao-Ching (2013). In the method, a laser light is projected into the monitored field of view, and the returning projected light section image is then analyzed to detect fire and smoke. The method assumes that if smoke appears within the monitoring zone created from the diffusion or scattering of laser light in the projected path, a colour CCD camera sensor receives a corresponding signal. The successive processing steps of the proposed algorithm utilize the spectral, diffusing, and scattering features of the smoke-filled regions (in YCbCr colour space) of the image sequences to determine the position of possible smoke in a video. Characterization of smoke is then carried out by a nonlinear classification method using a support vector machine. It is reported that experimental results in a variety of night-time conditions show that the proposed method can reliably detect smoke. However, the wavelength emitted by the employed off-the-shelf commercial laser diode is reported to be unstable due to fluctuations in the temperature and power supply.

In a recent study conducted by Hyuntae, Daehyun & Jangsik (2014), an outdoor smoke detection system that is robust to environmental change during daytime is proposed. Gaussian Mixture Model (GMM) is applied as background estimation algorithm to obtain candidate smoke object. Haar-features are extracted from candidate smoke region using computationally efficient Integral Image method after which blurring and morphological image processing techniques are applied. Finally, Adaboost algorithm is applied to detect smoke object. The proposed method's performance is reported to be computationally efficient and effective in detecting outdoor smoke. However, the method has only been tested on very few video clips; and only qualitative measures are provided.

Apart from studies in research community, commercial products related to fire detection using cameras are emerging in the market place. Popular commercial video-based fire detection systems include EYEfi, FireWatch, and ForestWatch. Other video-based smoke detectors that are currently available in the market also include SigniFire made by AxonX LLC, SFA produced by Fastcom Technology, FireVu made by D-Tec, and AlarmEye made by SimplexGrinnell. However, for understandable reasons, enough details are not provided about their algorithms.

5. Conclusion

While most of the challenges (such as variability of smoke density, lighting conditions, appearance that depends on the luminance conditions, colours of the scene, varying background , other moving objects and shadows; and unstable patterns) have been overcome using different novel techniques, many of the existing VFD approaches are still susceptible to false alarms. The impact of the false fire alarms might include declaration of emergency situation that may eventually lead to general loss of confidence in the detection system and major economic losses. It is expected that future work in efficient dynamic texture segmentation will help in reducing this false alarm. Also as it is illustrated by previous studies, a more robust smoke detection with high detection accuracies and low false alarm rates can be obtained by combining multi-spectrum video information using various image fusion techniques. Though such systems may be currently expensive, but they will be very useful with decrease in the costs of multi-spectrum image acquisition devices.

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