Fire Safety Journal 44 (2009) 1110–1115

Contents lists available at ScienceDirect

Fire Safety Journal

journal homepage: www.elsevier.com/locate/firesaf

Smoke detection in video using wavelets and support vector machines

Jayavardhana Gubbi *, Slaven Marusic, Marimuthu Palaniswami

ISSNIP, Department of Electrical and Electronic Engineering, The University of Melbourne, Victoria 3010, Australia

ARTICLE INFO

Article history:
Received 9 March 2009
Received in revised form
29 May 2009
Accepted 11 August 2009
Available online 2 September 2009

Keywords:
Smoke detection
Wavelets
Support vector machine
Video processing

ABSTRACT

Early warning systems are critical in providing emergency response in the event of unexpected hazards. Cheap cameras and improvements in memory and computing power have enabled the design of fire detectors using video surveillance systems. This is critical in scenarios where traditional smoke detectors cannot be installed. In such scenarios, it has been observed that the smoke is visible well before flames can be sighted. A novel method for smoke characterization using wavelets and support vector machines is proposed in this paper. Forest fire, tunnel fire and news channel videos have been used for testing the proposed method. The results are impressive with limited false alarms. The proposed algorithm is evaluated for its characterization properties using motion segmented images from a commercial surveillance system with good results.

1. Introduction

Automatic fire detection systems play a major role in the early detection and response of an unexpected fire hazard. Most sensor based fire alarms are designed for indoor use and are not applicable in outdoor scenarios and in large infrastructure settings such as aircraft hangers, large tunnels and exhibition buildings [1–3]. In 2006, Gottuk et al. [2] tested three commercially available video based fire detection systems against conventional spot systems in a shipboard scenario and found that the video based systems were far more effective in flame detection. In such scenarios, video based fire detection systems may be used effectively. These systems are economically viable as CCD cameras are already available for traffic monitoring [4] and surveillance [5] applications. Only the pattern recognition system has to be adapted for fire detection. Importantly, it is often observed that in outdoor scenarios, smoke is visible before the fire itself. This motivates us to build a system which detects smoke in the absence or presence of flame from a single frame of video.

The problem of video based fire detection has been recognized [1,6] but the rapid deployment of cameras for surveillance and availability of hardware resources in the past decade has enabled researchers to apply more concentrated efforts in this area. Several flame detection methods have been proposed and recently the focus has shifted to smoke detection. Most of the flame detection systems are either based on pixel intensity recognition or on motion detection. Toreyin et al. [7] carried out a comprehensive work on flame detection using wavelets and intensity based approaches. They tested their algorithm on many scenarios with impressive outcomes. Schultze et al. [8] analyzed dynamic characteristics of a flame using visual and audio features. Although they tested only one example, the approach is rather interesting. Marbach et al. [9] based their method on intensity based approaches with good results. Celik et al. [10] have proposed a new method of flame detection using a general color model to develop a rule based approach. These methods are targeted for flame detection and in general make use of the pixel color properties of the flame. Recently, Ko et al. [11] have proposed a non-linear classification method using support vector machines and luminescence maps, showing that the method is robust in several scenarios compared to features used earlier for flame detection.

Guillemant and Vicente [12] propose an algorithm based on fractals for smoke detection in forest fire scenario with impressive results. Thou-Ho et al. [13] propose a rule based system to detect smoke which is based on pixel intensity. They perform intensity based characterization of smoke. Xu et al. [14] use single stage wavelet energy and a back propagation neural network on a small dataset for smoke detection. The system requires high processing power which is unavailable in CCD camera networks. Piccinini et al. [15] propose a Bayesian framework for smoke motion detection using the wavelet energy of an 8×8 pixel block and intensity of the pixels. Vezzani et al. [16] propose a similar system in the context of ViSOR repository. Yang et al. [17] propose a support vector machine based approach using motion detection as the feature to detect the smoke contour. Recently, Yuan et al. [18] have reported a block by block approach based on chrominance

* Corresponding author. Tel.: +61 3 90358101; fax: +61 3 93471094.
E-mail addresses: jgl@unimelb.edu.au (J. Gubbi), slaven@unimelb.edu.au (S. Marusic), palani@unimelb.edu.au (M. Palaniswami).

0379-7112/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.firesaf.2009.08.003

and motion orientation. They propose a new fast algorithm for motion orientation estimation and test them on four videos. However, the chrominance based methods they use have a disadvantage in their dependence on the color of smoke. Also, the motion estimation algorithm is very time consuming in the context of smoke detection. All of these systems incorporate motion detection as a standard processing step. Ferrari et al. [19] have proposed a block based approach similar to the proposed approach for steam detection in oil sand mines. They use Wavelets and Hidden Markov Model for feature extraction and support vector machines for classification with very good accuracy of over 90%. However, the system is fine tuned to the oil sand application. Moreover, only steam is characterized in their approach where as this paper presents a novel algorithm for smoke detection which has the ability to detect smoke in various scenarios. Another important aspect of this work is the use of motion segmented images for smoke detection. Realistically, a smoke detection algorithm in commercially available CCD based systems has to run in parallel with many other surveillance processes. Hence, it is ideal to design a system incorporating the existing motion estimation methods or bypassing such motion estimation altogether. This forms the motivation for our work on characterizing smoke with robust and reliable features. The work is based on the characterization and detection of smoke observable from low quality fixed video surveillance, set at a distance from the potential fire location. The method is independent of atmospheric conditions at the time of filming—temperature, wind speed, wind direction and the time of the day. In this paper, we try to characterize smoke via a block based approach using discrete cosine transforms and wavelets respectively. We first evaluate a simple *k*-NN classifier with limited success and thus propose a final strategy to use wavelets along with a non-linear classifier such as support vector machines for smoke detection. We finally show the robustness of the system by testing it on motion segmented smoke images from a commercially available system.

Fig. 1. Forest fire smoke examples.

2. Methodology

The principal idea is to characterize smoke using efficient features and detection of the same using a suitable classifier by block processing. Basically, any single frame of a video stream is divided into small blocks of 32×32 pixels. Every block is checked for the presence or absence of smoke. The architecture is based on a standard pattern recognition approach with preprocessing, feature extraction and classification sub-units with training and testing phases.

2.1. Dataset and preprocessing

Seven bushfire videos were used for evaluating the proposed block based approach. Forest fire videos were captured in a forest scenario where the camera view encompasses land mass and clouds, where significant confusion is created due to color similarities between different elements of the scene and the feature of interest. An example image from the forest fire video is shown in Fig. 1. It can be clearly seen that the smoke disperses significantly at the top of the image which is an indication of a high wind scenario. There were seven such videos with a static camera and the input to our algorithm was a JPEG image from a frame of the video. The camera used was a normal CCD camera with low resolution, which is evident from the poor quality of the image in Fig. 1. Each video generated approximately 700 JPEG images. In the block based approach, the JPEG image is divided into 32×32 blocks and Fig. 2 shows the positive and negative samples in red and blue respectively. All the blocks which

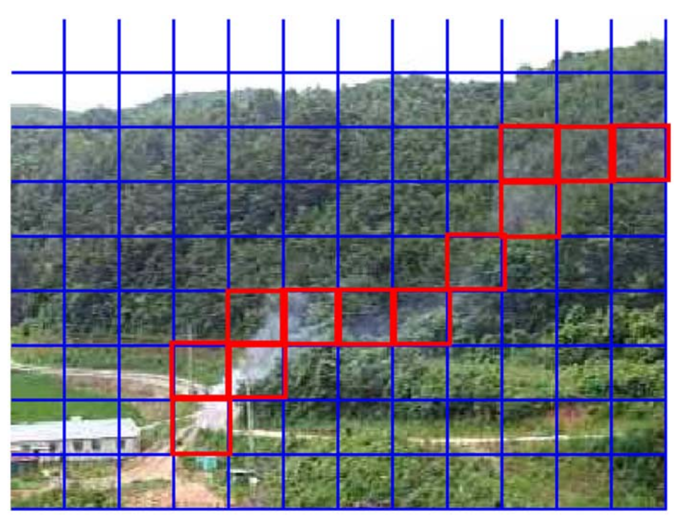

Fig. 2. Input image divided into 32×32 blocks. Red indicates blocks with smoke and blue indicates non-smoke blocks. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

contained smoke were considered as positive samples and the remainder as negative.

2.2. Feature extraction and classification

An image feature is a representation or an attribute of an image describing certain special characteristics of the pattern of interest. Feature extraction is defined as locating those pixels in an image that have some distinctive characteristics. Frequency domain features such as discrete cosine transforms (DCT) and wavelet transforms are used after preliminary experiments with gray level dependence matrix of the image. For classification, k-means classifier was used. However, the increase in the number of false positives motivated us to investigate the performance of non-linear classification methods. A properly trained feature and classifier could reduce the number of false positives by increasing the sensitivity as well as specificity. Hence to make the characterization method more robust we used the state of art classifier, support vector machines (SVM). In this section, the two feature generators and the two classifiers are briefly discussed.

2.2.1. Discrete cosine transforms (DCT)

The discrete cosine transform (DCT) is an orthogonal transform that de-correlates the image into spectral sub-bands of differing importance related to image's visual quality [20]. The DCT [21] is similar to the discrete Fourier transform but contains only real values in converting the image from the spatial domain to the frequency domain. Because of its energy compaction it is very widely used in data compression such as JPEG. The 2D discrete cosine transform is given by

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \tag{1}$$

where $\alpha(u)$ and $\alpha(v)$ for $u,v = 0,1,2\ldots N-1$ are defined by

$$\alpha(u),\alpha(v) = \begin{cases} \sqrt{\dfrac{1}{N}} & \text{for } u,v=0 \\ \sqrt{\dfrac{2}{N}} & \text{for } u,v\neq 0 \end{cases} \tag{2}$$

The first transform coefficient referred to as the *DC coefficient* is the average value of the image pixel intensities. Low frequency components represent the general shape and high frequency components represent edges and finer details in an image. The low frequency components are towards the top left and high frequency components are towards the bottom right of the block of transformed data. The DCT is applied to the image block and only the first 100 of the total transformed coefficients are retained after zigzag coding. Zig-zag scanning is used to include only low frequency data from each block as they store maximum information about the object. The total number of features in the feature vector of each object in the DCT is 100 coefficients from each image.

2.2.2. Discrete wavelet transform (DWT)

Wavelets [22,23] are mathematical functions that decompose the data into different frequency components and study each component with a resolution matched to its scale. This is a fast, linear, invertible orthogonal transform with the basic idea of defining a time-scale representation of a signal by decomposing it onto a set of basis functions, called wavelets. They are suitable for the analysis of non-stationary signals since it allows simultaneous localization in time and scale.

The continuous wavelet transform (CWT) of a function f using a wavelet function basis is defined by

$$f(a,b) = \frac{1}{\sqrt{a}}\int f(t)\Psi^*\left(\frac{t-b}{a}\right)dt \tag{3}$$

where $\Psi(t)$ is called the mother wavelet function, a is the scaling (compression or dilation) coefficient, b is the translating (shifting) coefficient and $1/\sqrt{a}$ is a normalizing factor which is applied to make the transformed signal have the same energy at every levels [24]. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

The discrete wavelet transform is based on sub-band coding. The DWT gives a time-scale representation of the digital signal using digital filtering techniques. The wavelet transform decomposition is computed by successive low-pass and high-pass filtering of the discrete time-domain signal based on the "Mallat algorithm" or "Mallat-tree" decomposition. The wavelet decomposition results in levels of approximated and detailed coefficients. The algorithm of wavelet signal decomposition is illustrated in Fig. 3:

$$[A_k, (H_i, V_i, D_i)_{i=1,\ldots k}] \tag{4}$$

where A_k is a low resolution approximation of the original image, and H_i, V_i, D_i are the wavelet sub-images containing the image details (detailed coefficients) in horizontal, vertical and diagonal directions at the i-level decomposition. A level 3 decomposition is shown in Fig. 4. The decomposition of k-level wavelet transform on the original image will be represented by $3k+1$ sub-images. This multi-resolution analysis enables us to analyze the signal in different frequency bands, thus providing information about any transient in the time domain as well as in the frequency domain.

There are a number of basis functions that can be used as the mother wavelet. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting wavelet transform. Depending on the application the appropriate mother wavelet has to be chosen for efficient working of the wavelet transform. Daubechies second order moments (db2), and Symlet third order (Sym3) have been chosen as mother wavelets for feature extraction in our analysis. After initial testing, Daubechies wavelet is chosen in all our experiments.

The fundamental idea of using the wavelet transform comes from the fact that it gives frequency information at different scales. Simply put, it will convert frequency components of a given image into various sub-bands by repeated decimation maintaining the spatial information. For characterizing smoke, this is very critical as it was observed that smoke behaves in completely

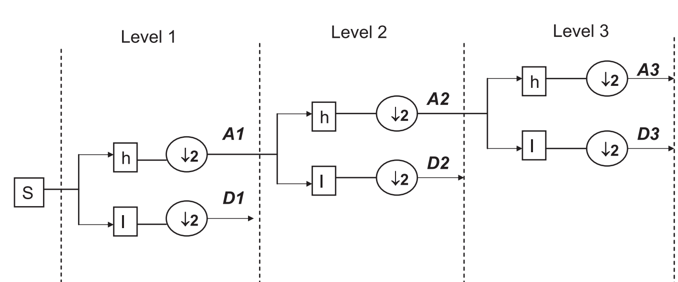

Fig. 3. Multi-resolution wavelet decomposition: l, low-pass decomposition filter; *h*, high – pass decomposition filter; ↓2, down – sampling operation. A1, A2, A3 are the approximated coefficient of the original signal (S) at levels 1, 2 and 3. D1, D2, D3 are the detailed coefficient at levels 1, 2 and 3.

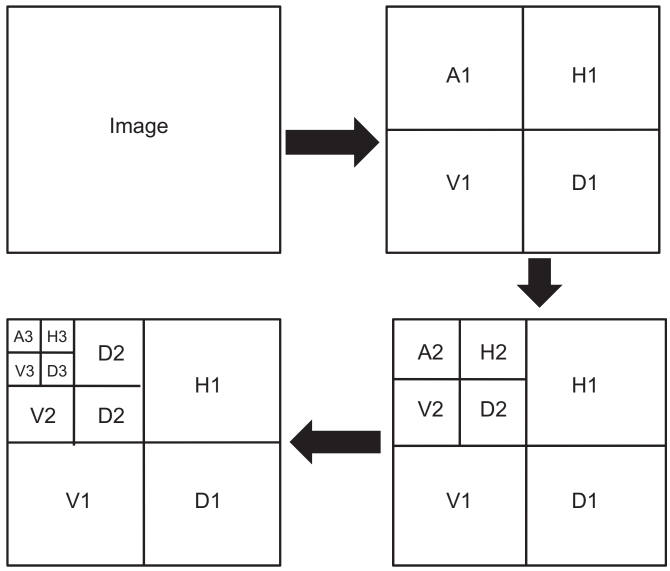

Fig. 4. Discrete wavelet transform multilevel (3 level) decomposition of an image.

unpredictable ways. In the sense that, in some cases it appears dense and uniform which leads to large low frequency components. In some cases smoke appears sparse and distributed which leads to large representation in high frequency components. As reported in [19], it can be imagined as a texture with multiple edges non-uniformly distributed. This is unlike most normal images, where the low frequency components are pre-dominant. In the case of an image, the orientation of the smoke also plays a major role depending on the wind direction. Taking all these behaviors into consideration, we considered all sub-bands at different levels from 1 to 6 for 64×64 blocks, 1 to 5 for 32×32 blocks and 1 to 4 for 16×16 blocks. After a rigorous analysis of features at different levels, we used three levels of wavelets decomposition. Unlike Ferrari et al. [19] who used only the second level, we found that the third and the first levels were also important for classification. This can be attributed to the fact that their focus was only on steam recognition and we are targeting a larger framework of gaseous substances including tunnel smoke and forest fire smoke. A similar decision about the orientation of smoke could not be made as it was found to be too variable. Hence all three detail sub-bands (vertical, horizontal and diagonal) were used in all three levels. As shown in Fig. 4, at each level the sub-image after transformation contains information in the horizontal, vertical and diagonal directions. Including all these coefficients as features is exhaustive and time consuming for processing. In order to reduce the number of features and give better representation, six derived features are calculated from the coefficients of the sub-bands. The six features chosen were arithmetic mean, geometric mean, standard deviation, skewness, kurtosis and entropy. In normal (non-smoke) images, these features follow a certain pattern which is quite different from images with smoke. For instance, kurtosis which measures the peakedness of a distribution increases in high frequency sub-bands due to the presence of many high frequency components in case of a smoke image. Similarly, in case of smoke images the skewness is more towards the left (called left skewness). However, one single feature could not classify smoke and non-smoke consistently. Hence all the features were retained and these were calculated for the horizontal, vertical and diagonal components at each level. This generates six features for each block in Fig. 4 which results in a total of 60 features for three levels. These 60 features are used as the input to the classifier.

2.2.3. k-Nearest neighbor (k-NN)

The nearest neighbor classifier is one of the simplest pattern classifier algorithms. In its classical manifestation, given a reference sample, $S_n = (X_i, Y_i), 1 \leq i \leq n$ the classifier assigns any input feature vector to the class indicated by the label of the nearest vector in the reference sample [25]. More generally, the k-nearest neighbor classifier maps any feature vector X to the pattern class that appears most frequently among the k-nearest neighbors. A major disadvantage of this method is its large computing power requirement, since for classifying an object its distance to all the objects in the learning set has to be calculated. In this study, the value of k is chosen to be three after empirical analysis, meaning the object will be assigned to the class most common among its three neighbors.

2.2.4. Support vector machines (SVM)

Support vector machines introduced by Vapnik [26] are a relatively new class of learning machines that have evolved from the concepts of structural risk minimization (SRM) [27] and regularization theory. They are also known as maximum margin classifiers as they simultaneously minimize the empirical classification error and maximize the geometric margin. A SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. SVM models are closely related to neural networks.

By combining max-margin classification and empirical risk minimization, using structural risk minimization, and also applying the kernel trick to achieve non-linearity, support vector machines are able to tackle highly complex classification tasks and generalize well without suffering from over-fitting or the so-called "curse of dimensionality". They are also mathematically tractable and have a unique global solution, both of which are highly desirable traits. The basic idea of SVM theory is to (implicitly) map the training data into higher dimensional feature space. A hyperplane (decision surface) is then constructed in this feature space that bisects the two categories and maximizes the margin of separation between itself and those points lying nearest to it (the support vectors). This decision surface can then be used as a basis for classifying vectors of unknown classification.

The SVMLight [28] implementation for support vector machines was used in all the experiments. The radial basis function (RBF) kernel given in Eq. (5) is used for testing the features:

$$K(x, y) = \exp\left(\frac{-\|x - y\|^2}{\gamma}\right) \tag{5}$$

3. Experimental results

As mentioned earlier, seven video streams of forest fire were used for testing the proposed method. A 10-fold cross validation was performed on all the available image blocks. There were approximately 140,000 image blocks with the ratio of positive to negative samples as 1:9. The image blocks were obtained by randomly selecting 250 image frames from each of the seven videos and manually tagging each frame. Every image frame comprised of 108 blocks as shown in Fig. 2. In this work all the analysis has been carried out on the G channel of the RGB image after analyzing performance of the other channels. The result of the block based approach is summarized in Table 1. As it can be seen, the combination of wavelets and support vector classifier resulted in consistent accuracies. Although the DCT resulted in reasonable results, the fact that the images were already stored in JPEG format, which utilizes lossy compression, did not perform as

Table 1
Results comparing DCT and wavelet features for block based approach.

	k-NN			Support vector classifier		
	Accuracy (%)	Sensitivity	Specificity	Accuracy (%)	Sensitivity	Specificity
DCT	68.88	0.69	0.69	63.21	0.57	0.64
Wavelets	76.16	0.53	0.79	88.75	0.90	0.89

Fig. 5. Some examples of motion extracted images.

well as wavelet features. For evaluating the proposed method, accuracy, sensitivity and specificity were used as defined:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{6}$$

where TP is the true positive, TN the true negative, FP the false positive, and FN the false negative. The *k*-NN classifier resulted in accuracies of 68.88% and 76.16% with DCT and wavelet features respectively. On the other hand, the support vector classifier resulted in accuracies 63.21% and 88.75% with DCT and wavelet features. Sensitivity of 0.9 and specificity of 0.89 resulting from the combination of wavelets and support vector classifier is much more attractive than accuracy results. This is because of the fact that it indicates a much lower incidence of false positives which is critical in a smoke detection scenario.

3.1. Testing using motion segmented images

The intention of the proposed method was to detect smoke with as little computation as possible. Once the support vector machine is trained, online testing is very quick using a visual C++ program on a PC. However, the number of blocks to test is quite high (108 per frame). Testing every block for smoke requires enormous computation. Most commercial systems already have a motion segmentation stage which segments smoke motion without the knowledge of that being smoke. Hence we decided to test the system on a motion segmented image from a commercially available surveillance system (*from iOmniscient Ltd*). It should be noted that such a system is already segmenting motion for other purposes and the proposed algorithm is not taking any extra time for motion segmentation. The forest video, news channel video and tunnel video were subjected to a commercial motion detector and the segmented images were used to test our algorithm. The motion detection created about 7500 JPEG images of varying sizes as shown in Fig. 5. After filtering similar looking images, 773 unique representative images were obtained, with 135 smoke images and 638 non-smoke images. This reduction was required to eliminate repetitive images which can skew the results of machine learning algorithms. The image size was normalized using bilinear interpolation to 32×32 after analyzing the effect of using different sizes such as 8, 16 and 64. At this stage, only the successful combination of wavelet features and support vector classifier was used for performance evaluation. As this dataset was very small due to motion segmentation, we performed two types of tests: (a) leave one out error; and (b) blind testing. A leave one out error of 8.53% (66/773) was obtained. In blind testing, the image set was randomly divided into two groups containing 603 training samples and 215 testing samples. The number of support vectors obtained because of training was 15% of the total input vectors. The truth table for one of the random blind tests is given in Table 2. As it can be seen in Table 2, the number of false positives is negligible.

Table 2
Truth table of blind testing motion segmented images.

	Predicted smoke	Predicted no smoke
True smoke	43	2
True non-smoke	2	168

Time taken by the classifier is a very crucial factor in smoke detection systems. For testing 215 samples, the feature extraction took 0.43 s and the classification stage took 0.22 s once the support vectors were loaded. In the case of block by block segmentation, the processing time including feature extraction and classification for every frame was 0.33 s which is comparable to the results reported by Ferrari et al. [19]. The training time was

85 s in the block based approach. However, the training process is off-line and its implication is negligible on the performance of the overall system.

4. Conclusion

A new approach based on wavelets and a support vector machine has been proposed for smoke detection. Characterization of smoke was carried out by extracting wavelet features from approximate coefficients and three levels of detailed coefficients. The system is implemented in visual C++ on a PC and is shown to work well using a block based approach as well as on motion segmented images. An excellent cross validation accuracy of over 90% with sensitivity and specificity of 0.9 and 0.89 respectively is obtained on videos taken of forest fire. This indicates that the 60 features extracted can efficiently represent smoke in the tested scenarios. The method has the flexibility to analyze smoke every few seconds using only a few frames rather than continuous monitoring. It can also be used with systems which have motion detection capabilities as discussed in Section 3. To check the robustness of the technique, motion segmentation was carried out on a forest fire video, a news channel video, a tunnel video and then input to the system. A leave one out error of 8.53% is obtained which is an indication that the recognition engine can be plugged into any commercially available surveillance system.

Acknowledgments

The authors acknowledge Dr. Rustom Kanga, iOmniscient Pty Ltd for data and feedback he provided during this work. This work was carried out under the DEST-ISL Project on Distributed Sensor Networks (CG080110) in collaboration with iOmniscient Pty Ltd, Sydney, Australia.

References

[1] V. Cappellini, L. Mattii, A. Mecocci, An intelligent system for automatic fire detection in forests, in: Third International Conference on Image Processing and its Applications, 1989, 1989, pp. 563–570.
[2] D.T. Gottuk, J.A. Lynch, S.L. Rose-Pehrsson, J.C. Owrutsky, F.W. Williams, Video image fire detection for shipboard use, Fire Safety Journal 41 (4) (2006) 321–326.
[3] Z. Xiong, R. Caballero, H. Wang, A.M. Finn, M.A. Lelic, P.Y. Peng, Video-based smoke detection: possibilities, techniques, and challenges, in: IFPA, Fire Suppression and Detection Research and Applications—A Technical Working Conference (SUPDET), 2007.
[4] V. Kastrinaki, M. Zervakis, K. Kalaitzakis, A survey of video processing techniques for traffic applications, Image and Vision Computing 21 (2003) 359–381.
[5] M. Shah, O. Javed, K. Shafique, Automated visual surveillance in realistic scenarios, IEEE Multimedia 14 (2007) 30–39.
[6] X. Cheng, J. Wu, X. Yuan, H. Zhou, Principles for a video fire detection system, Fire Safety Journal 33 (1) (1999) 57–69.
[7] B.U. Toreyin, Y. Dedeoglu, U. Gudukbay, A.E. Cetin, Computer vision based method for real-time fire and flame detection, Pattern Recognition Letters 27 (2006) 49–58.
[8] T. Schultze, T. Kempka, I. Willms, Audiovideo fire-detection of open fires, Fire Safety Journal 41 (2006) 311–314.
[9] G. Marbach, M. Loepfe, T. Brupbacher, An image processing technique for fire detection in video images, Fire Safety Journal 41 (4) (2006) 285–289.
[10] T. Celik, H. Demirel, Fire detection in video sequences using a generic color model, Fire Safety Journal 44 (2) (2009) 147–158.
[11] B.C. Ko, K.H. Cheong, J.Y. Nam, Fire detection based on vision sensor and support vector machines, Fire Safety Journal 44 (3) (2009) 322–329..
[12] P. Guillemant, J. Vicente, Real-time identification of smoke images by clustering motions on a fractal curve with a temporal embedding method, Optical Engineering 40 (4) (2001) 554–563.
[13] C. Thou-Ho, Y. Yen-Hui, H. Shi-Feng, Y. Yan-Ting, The smoke detection for early fire-alarming system based on video processing, in: International Conference on Intelligent Information Hiding and Multimedia Signal Processing, 2006, IIH-MSP '06, 2006, pp. 427–430.
[14] Z. Xu, J. Xu, Automatic fire smoke detection based on image visual features, in: International Conference on Computational Intelligence and Security Workshops, 2007, CISW 2007, 2007, pp. 316–319.
[15] P. Piccinini, S. Calderara, R. Cucchiara, Reliable smoke detection in the domains of image energy and color, in: 15th IEEE International Conference on Image Processing, 2008, ICIP 2008, 2008, pp. 1376–1379.
[16] R. Vezzani, S. Calderara, P. Piccinini, R. Cucchiara, Smoke detection in video surveillance: the use of visor (video surveillance on-line repository), in: Proceedings of the 2008 International Conference on Content-based Image and Video Retrieval, Niagara Falls, Canada, ACM Press, New York, 2008.
[17] J. Yang, F. Chen, W. Zhang, Visual-based smoke detection using support vector machine, in: Fourth International Conference on Natural Computation, 2008, ICNC '08, vol. 4, 2008, pp. 301–305.
[18] F. Yuan, A fast accumulative motion orientation model based on integral image for video smoke detection, Pattern Recognition Letters 29 (2008) 925932.
[19] R.J. Ferrari, H. Zhang, C.R. Kube, Real-time detection of steam in video images, Pattern Recognition 40 (3) (2007) 1148–1159.
[20] K.R. Rao, P. Yip, V. Britanak, Discrete Cosine Transform: Algorithms, Advantages, Applications, Academic Press, Boston, 1990.
[21] N. Ahmed, T. Natarajan, K.R. Rao, On image processing and discrete cosine transform, IEEE Transactions on Computers C-23 (1974) 90–93.
[22] Y.T. Chan, Wavelet Basics, Kluwer Academic Publishers, Dordrecht, 1995.
[23] F.W. David, An Introduction to Wavelet Analysis, Birkhauser, Basel, 2002.
[24] D. Bedekar, A. Nair, D.G. Vince, Choosing the optimal mother wavelet for decomposition of radio frequency intravascular ultrasound data for characterisation of atherosclerotic plaque lesions, in: Proceedings of the SPIE Conference Record, vol. 5750, 2005, pp. 490–502.
[25] S.R. Kulkarni, G. Lugosi, S.S. Venkatesh, Learning pattern classification—a survey, IEEE Transactions on Information Theory 44 (6) (1998) 2178–2206.
[26] V. Vapnik, Statistical Learning Theory, Springer, New York, 1995.
[27] C.J.C. Burges, A tutorial on support vector machines for pattern recognition, Journal of Knowledge Discovery and Data Mining 2 (1998) 121–167.
[28] T. Joachims, Making large-scale svm learning practical, in: Advances in Kernel Methods—Support Vector Learning, 1999.