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REAL TIME IMAGING ACQUISITION AND PROCESSING SYSTEM TO IMPROVE FIRE PROTECTION IN INDOOR SCENARIOS

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Abstract: This paper proposed a new method to detect fire and flame in video sequences by processing the data recordedusing a common camera monitoring a large or open space. Flame flickering process is modelled by means of two kinds of feature representations. One is the pixel colour value variation, and the other is the contour shaping information with time. Both of these temporal cues provide discriminating power of fire regions. Then the population hidden Markov models are utilized to model the ordinary motion and colour cues. Markov models could represent the fire flame and flame colored ordinary moving objects. So it is used to distinguish flame flicker process from motion of flame colored moving objects. These clues are combined to reach a final decision. The experimental results show the promising performance of the proposed method.

1 INTRODUCTION

Fires could cause huge material damage and often lead to lots of human casualties. In order to avoid or reduce the loss of fire disaster, the fire detection and warning systems are widely used and of a necessary requirement for new buildings especially. If the fire flame could be detected at initial phase as early as possible, the loss would be limited to the minimum extend. Conventional smoke and fire detectors usually fail at a far distance or in large building spaces. In recent years, with the rapid development and deployment of video surveillance systems, the CCD or CMOS cameras are considered as the most advanced technology for automatic fire monitoring and detection.

Traditional fire detection techniques are frequently using particle sensors, temperature sensors and light reflection sensors, etc. During the past decades, video-based fire detection methods are developed and investigated widely. An important advantage of using video sequence data in fire detection field is the ability to cover a wide range in large and high-open spaces. Generally, video-based fire detection includes three main steps. Preprocessing of video data is the first step tocompensate for some known variability sources, such as camera hardware, illumination and so on. Feature extraction is the second step for the detection of fire or flame target. The fire should be characterized using a kind of computation maps raw data to a specific set of

parameters. The last step is to use classification
algorithms by means of inputting the computed features and outputting the decision regarding the fire target's presence. Supervised machine learning related algorithms, such as support vector machine (SVM).

This work is supported by Beijing Municipal Education Commission Nature Science Foundation and National Nature and neural network (NN) are trained on a data set of extracted features from video data and ground truth. Existing fire detection methods are mainly based on the colour and motion information in video sequences. A generic colour model is proposed to classify flame pixels. This colour model is constructed in YCbCr colour space, and consequently performs better to distinguish luminance from chrominance. Other related research literatures could be found in it. In the motion regions are segmented through localizing the flickering and edge-blurring pixels position. The usual background subtraction techniques and wavelet transformation methods are used to extract these image features. In the smoke pixels are found via the fusion of chromaticity based static decision rule and diffusion based dynamic characteristic rule. In the proposed fire detection method integrates the knowledge of flickering extraction, contour initialization and classification in a heuristic and empirical way. In the temporal varietyof flame geometry is considered to discriminate fire frombackground illuminations, such as artificial lights, sun lights, or light reflections and so on. Then the false flame detection rate is reduced.

However, video based fire detection usually is limited by surrounding situations and depends on data preprocessing techniques to a certain extent. As mentioned in it, many natural objects have similar attributes with fire and therefore might be often detected as flames mistakenly. For example, the sun shining, car lighting and other kinds of lights or light reflections on various surfaces could behave or flicker like fire. As for that reason, dynamic texture analysis is applied to the classification of video sequences containing flame, smoke, and so on. Fire behavior is modeled through using multiple spatio-temporal features and then dynamic texture analysis is employed in each candidate region with a linear dynamical system approach. In the changes between adjacent frames areanalysed by means of low-level features predicting potential fire regions. The colour cues, area size, surface coarseness and boundary roughness, and so on, are taken into account to evaluate the behavior change and the results are generated with the Bayes classifier for robust fire recognition.

Furthermore, a hierarchical Bayesian network is proposed in to detect fire using intermediate nodes, in which node there are four probability density functions. These functions are formed for evidence and modeled from the red colour and high frequencies information in a wavelet transform. Later on, a video-based fire detection system combining the colour, spatial and temporal information is proposed in it. In this system, the video sequences are divided into spatio-temporal blocks and then covariance based features are extracted, which render out both the spatial and temporal attributes of the flame region. Also, the combination of different spatio-temporal features is used to detect fire as proposed in. In order to determine the fire and nonfire regions, SVM classifier and rule-based approaches are adopted and investigated for a better result. According to the aforementioned proposals, we notice the temporal turbulent of flame features. As is known, the value of flame flicker frequency is around 10Hz and varies in time. Hence the temporal variation of fire features could be regard as random events. The Markov model is then appropriate to represent the flame flicker process. During the burning process, the fire region usually keeps waving and size-varying. Based on this fact, we utilize the colour and contour feature and model their temporal variation using population Hidden Markov Models (pHMMs). The colour region model and contour variation model shares the

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same transition probabilities.
The rest of this paper is organized as follows. The feature extraction method and the detection of candidate fire regions are presented in Section 2. Section 3 describes the pHMMs framework of modelling the region variations. The experimental results are discussed in Section 4, while conclusions are drawn in Section 5.

2 FEATURE EXTRACTION

According to the previous research works, fire features could be extracted from several classical aspects. In this paper, we choose the colour space and contour flickering as the feature source, both of which are typical of temporal information.

2.1 Fire Colour Area Extraction

The segmentation of fire region from a video frame is the first requirement to the fire detection algorithms. Hence, the choice of colour model is an important factor. The video sequences from colour cameras are RGB image data naturally. In this work, we transform the pixel's colour into the HSI space. HSI colour model is composed of hue (H), saturation (S), and intensity (I, or brightness), in which H denotes the dominant colour from human vision, saturation represents the percentage of white light mixed in a specific colour. HSI model tries to render the colour sensing properties in a human natural way. The H and S components are mainly derived from scene imaging in human vision system.
According to the calculated values of (H, S, I), each pixel is determined to be a flame or not with a predictor. So, the predicting model need be trained from a pixel data set. The parameter values in the model could be obtained from a SAS statistical package. In this work, we select 20 images to train the flame predictor model. The leave-one-out validation strategy is used, and during every iteration two of these images are chosen to model training data, the rest is for testing. A clear and high discriminating image could meet the requirement, where the fire region is easy to be segmented. For example, Figure 1 shows an appropriate picture.

Fig 1. A sample image

From the training pictures, we select two thousand pixel points randomly as the training data set. The (r, g, b) values of these pixels are transformed into (H, S, I) model. These points are all located within the fire rectangle area marked manually. Then, we calculate the statistical description and correlation matrix of the data set respectively. From the result, the negative H, S and positive I denotes the flame pixel. The histograms of HSI colour model are illustrated in Figure 2. It is shown that component I is more helpful to detect the fire points. In addition, the black smoke could not be neglected in the very early phase of fire process. In order to find the smoke pixel candidate, we need to calculate the smoke histogram template from training images. In this work, such a colourhistogram is generated through counting the appearance of fire smoke

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in sequential video frames. Then the position of
fire could be determined by the centroid of gravity of maximum degree area. A fact found here is that if smoke appears, the grey level histogram tends to concentrating without the relation of smoke colour

.

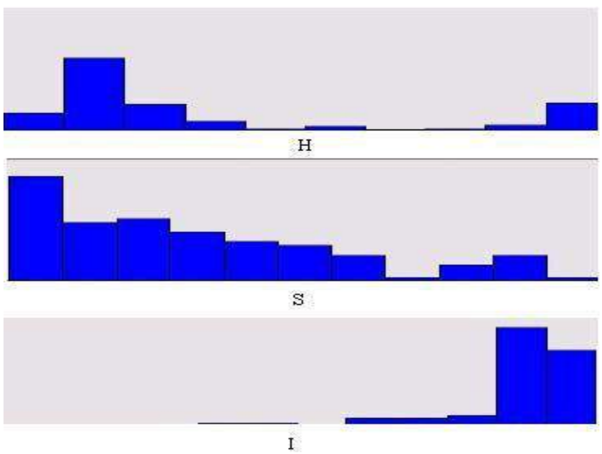

Fig 2. Histogram of H, S and I component

2.2 Temporal Fluctuation of the Contour

It can be seen that the fire does not appear in a fixed area from the videos. The contour of fire region is flickering with time. We could use the edge operator to extract the contour of fire colour area. The algorithm of edge detection is based on the analysis of colour contrast in an image. In this work, the contour data is represented using polar coordinate system. Any point on the contour is denoted by an angle θ against the horizontal axis and a distance r between itself and the centre point.

The results of edge detection compose of the contour of fire. These edge points are transformed into polar coordinate system. For a given video sequence, the point numbers included in a contour extracted from all frames are normalized to the same value. Then, for a given period of time, a fluctuation data could be obtained as a space-time data. Next, we adopt the two-dimensional Fourier transform and the normalization of the Powerto analyse the frequency distribution. When comparing the frequency component from fire light and artificial light, the result shows the obvious difference, as illustrated in Figure 3. Hence, the temporal information of flame flickering could right be used to detect fire.

According to the distribution pattern, it is not hard to distinguish fire flame from artificial light. However, the variation of flame contour shape occurs from many aspects, such as the burning material, the wind, the air flow rate and so on. Consequently, the position of the concentration and the pattern of the distribution might change for different observing areas. So, a generalization facility of flame contour pattern should be learned and consider all possible situations.

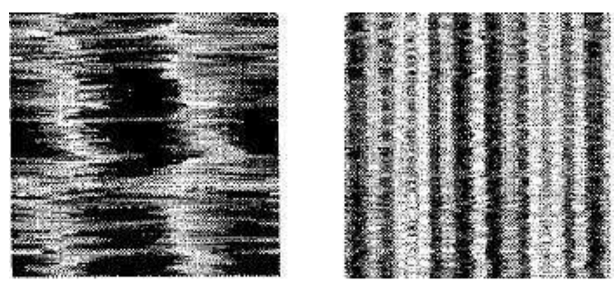

Fig 3. Frequency difference of contour

3 FRAMEWORK BASED ON pHMMs

Fire detection is actually a two-class problem. For a given pixel block, we just decide whether it belongs to the fire region or not. In this work, linear chain structure is utilized to simulate the temporal relation of the fire dynamic process. When the sequence number is bigger than one, define n is the number of sequences.

In order to make an optimization further, the zero point of the gradient is sought out.

Therefore, F could be maximized with the limited memory quasi-Newton algorithm. For decoding index sequences, we use maximal marginal posterior probability for each frame in population parametric space.

4 EXPERIMENTS

The proposed fire detection method is validated on six fire video sequences, including several conditions. Three of them are from daytime, and the rest is from night time.The total average detection rate can reach 96.4% as shown above. Such a result is encouraging and promising. For the indoor environment of video 1 and video 4, the detection method performs better than others. In addition, the videos used for experiments contain complex background and the proposed method still could keep a high correct rate over 90%. So, the temporal information of fire is deserved to have more attentions. 5 CONCLUSION In this paper both colour feature and contour feature are considered and modeled with the temporal characteristics. Based on these two variation models, we construct a pHMMs framework to train and learn the states transformation probabilities. The method is tested on six diverse video sequences. The experimental results show that the method could achieve more than 97% correct detection rate.

EXISTING METHOD AND DRAWBACKS

1. FIRE SENSOR based approach used currently in market.
2. GSM and GPS based E-Health

Fire sensor will detect fire within short distance. To cover more area need more fire sensors.

All the Techniques will carry only minimum information also limited distance.

PROPOSED METHOD

The color models are extracted using a statistical analysis of samples extracted from different type of video sequences and images. The extracted models can be used in complete fire/smoke detection system which combines color information with motion analysis.

After detection of fire it has to be intimated through E-mail Alert.

PROPOSED ALGORITHM

1. Statistical model build by foreground accumulation image.
2. Optical flow Calculation
3. Motion feature discriminating model

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