Proceedings of the 18th IEEE International Conference on Image Processing, 11-14 Sept. 2011, Brussels, Belgium, Pages 1741 - 1744

A NON-TEMPORAL TEXTURE DRIVEN APPROACH TO REAL-TIME FIRE DETECTION

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ABSTRACT

Here we investigate the automatic detection of fire pixel regions in conventional video (or still) imagery within real-time bounds. As an extension to prior, established approaches within this field we specifically look to extend the primary use of threshold-driven colour spectroscopy to the combined use of colour-texture feature descriptors as an input to a trained classification approach that is independent of temporal information. We show the limitations of such spectroscopy driven approaches on simple, real-world examples and propose our novel extension as a robust, real-time solution within this field by combining simple texture descriptors to illustrate maximal ~98% fire region detection.

***Index Terms*—** fire detection, texture, real-time, non-temporal

1. INTRODUCTION

A number of factors have driven forward the increased need for fire (or flame) detection within video sequences for deployment in a wide variety of automatic monitoring tasks. The increasing prevalence of industrial, public space and general environment monitoring using security-driven CCTV video systems has given rise to the consideration of these systems as secondary sources of both initial fire detection (in addition to traditional smoke/heat based systems). Furthermore, the on-going consideration of remote vehicles for fire detection and monitoring tasks [1, 2] adds further to the demand for autonomous fire detection from such platforms themselves move towards autonomous navigation and tasking [3]. In the latter case, attention turns not only to the detection of fire itself but also its internal geography of the fire and temporal development [4].

Prior work in area concentrates itself either on the use of a purely colour based approach [5, 6, 7, 8, 9, 4] or a combination of colour and high-order temporal information [10, 11, 12, 13]. Early work emanated from the colour-threshold approach of [5] which was extended with the basic consideration of motion by [10]. Later work considered the temporal variation (flame flicker) of fire imagery within the Fourier domain [11] with further studies formulating a Hidden Markov Model problem [12]. More recently work considering the temporal aspect of the problem has investigated time-derivatives over the image [13]. Although flame flicker is generally not sinusoidal or periodic under all conditions, a frequency of 10Hz has been observed in generalised observational studies [14]. As such, [15] considered the use of the wavelet transform as a temporal feature. In later applications [7] we still see the basic approaches of [10] underlying colour-driven approaches although more sophisticated colour models based on a derivative of background segmentation [9] and consideration of alternative colour spaces [8] are proposed. In general recent works report ~98-99% detection rates with frame rates in the region of 10-40 fps on relatively small image sizes (CIF or similar) [9, 8].

Notably work on the application of machine-learning type classification approaches to the fire detection problem is limited with the work of [16] considering a colour-driven approach utilising temporal shape features as an input to a neural network and similarly the work of [17] utilising wavelet coefficients as an input to an SVM type classifier. The majority of early work purely considers colour-based classification within RGB colour-space [5, 10] with these approaches seeing further merit in later work [13, 15, 4]. Further refinements considered alternative chromaticity, HSV or YCrCb colour-space formulations [6, 8, 17]. Here, by contrast to previous classifier-driven work [16, 17, 4], we consider a non-temporal classification model for fire regions within the image based on a novel combination of HSV colour and statistical texture features [18]. We show that comparable detection results are achievable using similar classification approaches to [16, 17] without consideration of temporal information making the proposed approach applicable to still or video imagery alike.

2. FEATURE EXTRACTION

As previously discussed, prior work on the automatic detection of fire within imagery centres around the consideration of colour, movement (or scene change) and short-order temporal characteristics [12, 15, 17, 16]. Although, an increasing range of generalized object recognition approaches are becoming prevalent for objects of varying visual complexity [19], the target deployment of an automatic vision-based fire-detection system has an integral real-time requirement. To this end, it is the simpler detection strategies that are achievable within real-time bounds that come to prominence. Here we investigate the strength of simple, non-temporal colour spectroscopy based approaches [5, 10], illustrate their weaknesses (Section 4.1) and propose an combined texture and colour based feature descriptor as an input to a trained classifier based detection/decision boundary (Section 4.2) .

2.1. Colour Features

In a similar vein to the prior work of [6, 17] we utilise a perceptual colour-space, namely HSV (Hue, Saturation, Vari-

Fig. 1. Example of fire image separated into HSV colour channels (H with false colour added)

ance), representation for our colour features [20]. In contrast to early work on fire detection [5, 10], the use of an HSV colour representation allows us to isolate the illumination component of the scene (Variance channel) and the consideration of image pixel characteristics corresponding to fire within the Hue / Saturation channels alone (see example - Figure 1). Here the remaining Hue and Saturation channels are quantized as 10 element normalised histograms (per channel) for input as features for classification.

2.2. Texture Features

In addition to these summary colour features (Section 2.1), we also employ texture features within the fire detection problem. From the example of Figure 1 (top left) the nature of texture within such fire imagery is clearly apparent within the original RGB image. Its importance within the visual characteristics of fire is further supported by a) the flame frequency observations of [14] and b) the temporal nature of other work within the field [10, 11, 12, 13]. Both suggest that a given image frame within a fire sequence *(i.e. "snap-shot")* will contain statistical variation inherent of its nature that (in earlier works) have been integrated over time for identification purposes. Furthermore an examination of an extracted (ground truth) fire example as a distribution in both RGB and HSV space (Figure 2) suggest that this statistical variation is indeed apparent within a very limited subs-space of the colour palette. With this in mind we look to utilize the established Grey Level Co-occurrence Gray Matrix (GLCM) texture features to capture this indicative and compact statistical texture variation [18].

The GLCM is an adjacency matrix indexed by pixel intensity values calculated by considering pairs of pixels at a certain relative spatial distance, d, in all or a subset of the $\{N, NE, E, SE, S, SW, W, NW\}$ orientations with the im-

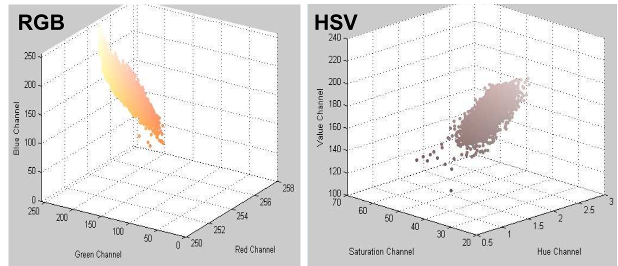

Fig. 2. Typical fire pixel distribution in RGB and HSV colour-space

$$Energy = \sum_i \sum_j G(i,j)^2$$
$$Entropy = -\sum_i \sum_j G(i,j) \log_2 G(i,j)$$
$$Contrast = \sum_i \sum_j (i-j)^2 G(i,j)$$
$$Homogenity = \sum_i \sum_j \frac{G(i,j)}{1+|i-j|}$$
$$Correlation = \sum_i \sum_j G(i,j) \frac{(i-u_i)(j-u_j)}{\sqrt{\sigma_i^2 \sigma_j^2}}$$
$$\text{where } u_i = \sum_i \sum_j iG(i,j),\ u_j = \sum_i \sum_j jG(i,j)$$
$$\sigma_i = \sum_i \sum_j G(i,j)(i-u_i),\ \sigma_j = \sum_i \sum_j G(i,j)(j-u_j)$$

Table 1. GLCM Summary Statistics

age [18]. Each normalized GLCM entry, $G(i, j)$, specifies the probability of finding a pixel of value j at spatial separation d from a pixel of value i in a given orientation. From each GLCM a range of summary statistics can be used to characterise the texture distribution captured by the matrix. In order to reduce computation, and representational redundancy, we calculate five such summary statistics (see Table 1) in the $\{E, SE, SW, S\}$ orientations resulting in the use of a 20 element texture descriptor (with $d = 1$). From our review of literature, this consideration of texture is novel within prior fire detection work with authors instead opting for additional temporal features to boost detection of otherwise colour-driven approaches [5, 10, 6, 11, 12, 15, 13, 2, 9, 7, 17, 8, 16, 4].

3. FEATURE CLASSIFICATION

Feature classification is performed based on a two stage approach:- a) isolation of candidate fire pixel regions using a basic colour spectroscopy approach [5, 6] and b) combined colour-texture classification of these regions using a trained classification approach. This two stage approach reduces the computation required for texture descriptor calculation by limiting such calculations to the regions identified by colour spectroscopy in the first stage thus aiding real-time performance.

3.1. Fire Region Isolation

Candidate fire regions within an RGB image are initially isolated based on an empirical colour spectroscopy rule-set derived from the earlier combined work of [5, 6]:

1. $R > R_T$
2. $R > G > B$
3. $S > (S_T(255 - R))/R_T$

where $\{R, G, B\}$are the channels of the RGB image respectively, S is the saturation channel of the HSV colour-space equivalent, R_T is the red channel threshold (range: $\{115 \rightarrow 135\}$ [6]) and S_T is the saturation channel threshold (range: $\{55 \rightarrow 65\}$ [6]). If all rules return true a given pixel is assigned as a candidate fire region pixel. These isolated candidate regions are then post-processed using morphological closing [20]. This approach can additionally be supplemented by simple frame differencing as required.

3.2. Colour-Texture Classification

The combined colour-texture descriptor consisting of both Hue and Saturation channel histograms (10 elements per channel) and the 20 element GLCM texture descriptor is used as an input to both regular decision tree (post-pruned) and neural network classifiers [21]. Classifier training is performed using k-fold cross-validation over 1194 example images (class split 50/50: $\{fire/non-fire\}$, $k = 8$) with testing performed over an isolated set of 53 video sequences varying in day/night, illumination, camera source and fire combustible etc. (each > 1 minute in length, evaluation on a per image frame basis). Both classifiers are experimental tested over varying levels of complexity (decision tree - max tree depth, neural network - number of hidden nodes). Decision tree construction used the CART algorithm whilst back-propagation was used for neural network training [21]. Principle Components Analysis (PCA) was subsequently used to identify a dimensionality reduction 36 $\rightarrow$ 30 [20] and the performance of the two classification approaches with and without this reduction compared.

4. RESULTS

4.1. Colour Spectroscopy

Colour spectroscopy alone [5, 10] is a weak non-temporal approach for the detection of fire pixels within an image. This is illustrated in the classical example of Figure 3 where we see the identification of both fire and (false positive detection) of fire appliance (engine) as fire regions within the image. The examples of Figure 7 A-C are similarly mis-classified by colour spectroscopy alone (but not by extended 2-stage classification).

4.2. Colour-Texture Classification

By contrast in Figure 4 (from the same video sequence as Figure 3) we see the isolation of the true fire pixel regions (Figure 4, red highlighted regions) as a subset of those identified by colour spectroscopy alone (Figure 4, green and red highlighted regions). An example of using colour spectroscopy

Fig. 3. Original image (left) and corresponding fire pixels regions detected using colour spectroscopy (right).

Fig. 4. Fire pixels regions detected using 2-stage colour spectroscopy and decision tree classification (red), single-stage colour spectroscopy only (green)

for initial candidate region identification and a trained neural network classifier for final fire detection (i.e. secondary confirmation) is shown in Figure 5.

Empirically a post-pruned decision tree classifier with a maximal tree depth of 9 was found to give optimal performance. The mean test performance of this approach over 8 cross validation folds was 87.83% with ~7% false positive detection. Maximal detection of 97.8% was achieved using this approach over all cross-validation subsets. A neural network classifier, experimentally optimised to a final 3-layer and 25 hidden node topology, resulted in 83.09% mean successful detection with a ~8% false positive rate over 8 cross-validation folds. Maximal detection using this neural network approach was 88.1%. The use of PCA dimensionality reduction was found to only increase the successful detection rates by a marginal ~1-2% using either selected approach.

Using the decision tree approach, 360x288 resolution images within a video sequence could be classified at ~12fps whilst classification using the neural network approach achieved ~6fps. This mild-reduction in real-time performance compared to prior classification work on this problem [17, 16] is attributable to texture descriptor calculation.

Further examples of successful fire detection are shown in Figure 6 whilst in Figure 7 we see both the successful non-fire classification of regions commonly mis-classified by colour spectroscopy based approaches [5, 10] (Figure 7 A-C - red/yellow/orange objects and high illumination/saturation solar reflectance) and additionally a case where our proposed colour-texture feature approach itself fails due to a combination of smoke/flame transparency artifacts (Figure 7 D).

Fig. 5. Fire pixels regions detected using neural network classification (red)

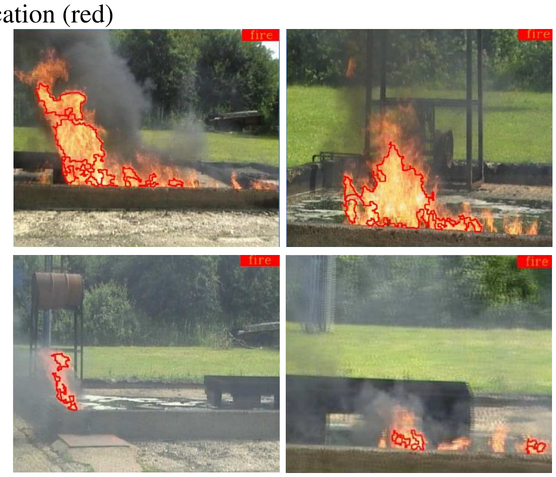

Fig. 6. Fire pixels regions detected using decision tree classification (red)

5. CONCLUSIONS

We successfully show comparable classification results, using simpler trained classifier techniques, to recent prior work in the field [17, 16] without any requirement for temporal information. The proposed technique can be applied to both video and still imagery alike and offers a more robust fire detection capability than approaches reliant only upon colour features [5, 6, 7, 9, 8]. Within the framework proposed the impact of texture feature calculation on real-time performance is minimal and the approach remains within the bounds of deployable use. Future work will investigate the use of alternative texture descriptors and the possible use of texture descriptors to improve the performance of state of the art temporal fire detection approaches.

Acknowledgments: The authors would like to thank Cranfield University Airport Fire and Rescue Service for their support in this work.

Fig. 7. Successful non-fire detection (A-C) and false negative example (D)

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