A Model Integrating Fire Prediction and Detection for Rural-Urban Interface

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***Abstract*— This paper proposes a model that integrates new fire detection and fire prediction techniques for the rural-urban interface area. The model aims to predict fire risk from weather parameters, and to detect smoke using video monitoring systems as smoke is the early sign of fire. Further, the fire danger index (FDI) provided by the prediction algorithm would be utilized to enhance the certainty of fire detection and reduce false alarm rates. Experimental results illustrate that our prediction algorithm successfully predicts fire risk on a five-point scale with mean accuracy of 94.92% and the detection algorithm more effectively detects smoke compared to other algorithms by achieving 97% average accuracy.**

Keywords—Fire Model, Fire Prediction, Fire Detection, Alarm Verification, Rural-Urban Interface

I. Introduction

Bushfire is one of the most devastating hazards that cause not only catastrophic loss of lives but also environmental, social and economic damages. With the fast growing urbanization, numerous dwelling houses and business properties are being established in the rural-urban interface (RUI) area which could potentially be affected and damaged by bushfires. Recently some destructive bushfires at RUI area occurred that were a threat to the communities such as: Florida in 1998, southern California during 2003 and 2007, Greece in 2007, Victoria, Australia in 2009, Tasmania during 2013, and New South Wales, Australia in 2013 [1]. Bushfires bring severe destruction for the people living in the interface area. The primary attack at this type of interface area is mainly caused by the smoke and toxic gases from flames as well as firebrands produced by bushfires. Following this, the elements of residential house, garden vegetation, and dry forest trees help to propagate the fire through the urban area. Over the last 10 years, over 4000 houses destroyed and nearly 200 casualties occurred by some major bushfires of Australia [2]. There is a significant need to design a comprehensive and scientific approach in reducing the exposure of bushfire for the RUI communities [1]. For this reason, quantifying the losses of lives, structures, and forests affected by the bushfires in the rural-urban area is a vital context to build a fire model. The model should include the prediction of upcoming fire hazards as well as early detection and suppression of fire using prediction data. In general, Fire prediction systems provide fire danger index (FDI) that corresponds to the number of fires that could occur in definite number of days. This prediction technique requires monitoring a number of environmental parameters or features in a continuous basis during the days used in the experiment. Further, video surveillance systems are among the effective ways of fire detection for open spaces.

Over the last few years, a number of papers about fire prediction have been published. A physical model to predict the spread and intensity of forest and range fires was demonstrated in [3]. The model projected fire spread and intensity under the expected topographic conditions for uniform continuous fuels. However uniform fuel is not practical in all situations. In [4] the authors suggested a nonlinear predictor using passive infrared sensors. Alonso et al. defined a neural network based fire risk predictor and they claimed high accuracy of their system [5]. Despite this level of accuracy, the system is not applicable for real time application. Safi et al. [6] and Vasconcelos et al. [7] applied a similar neural networks based approach for forest fire prediction utilizing geographical and meteorological variables. Support vector machines (SVM) and artificial neural networks (ANN) were integrated to predict forest fires by exploiting relative humidity and cumulative precipitation [8]. In contrast, this system was tested for a limited time span and was confined to one specific area. A data mining approach was reported to predict forest fires in [9, 10] that used metrological datasets. In summary, the main problems of current prediction system include: (i) using only supervised algorithms with limited capability (ii) most works did not consider the correlation between weather parameters and fire ignition.

Considering fire detection various approaches have been adapted so far for detection of smoke and fire in video sequences. Fire color information and frame difference were utilized to detect candidate fire regions and support vector machines (SVM) were used for fire verification [11]. But frame difference does not provide a stable candidate region selection and furthermore high missed detection rates were observed when scene background had bright colors similar to the appearance of fire. Gaussian Mixture Models (GMM) were used in [12] to extract fire candidate regions which resulted in better performance compared with color information and frame difference methods. In [13] a fuzzy logic based approach for detecting smoke and flame candidate regions is proposed which utilized spectral, spatial and temporal features to detect flame and smoke, but failed to increase the system reliability in case of environments that contain complex movements of various objects. Furthermore, a Fuzzy C-Means (FCM) method was employed to segment smoke candidate regions based on color as discussed in [14, 15]. A recent review on video fire detection has analyzed currently available smoke and fire detection algorithms and concluded that color based detection

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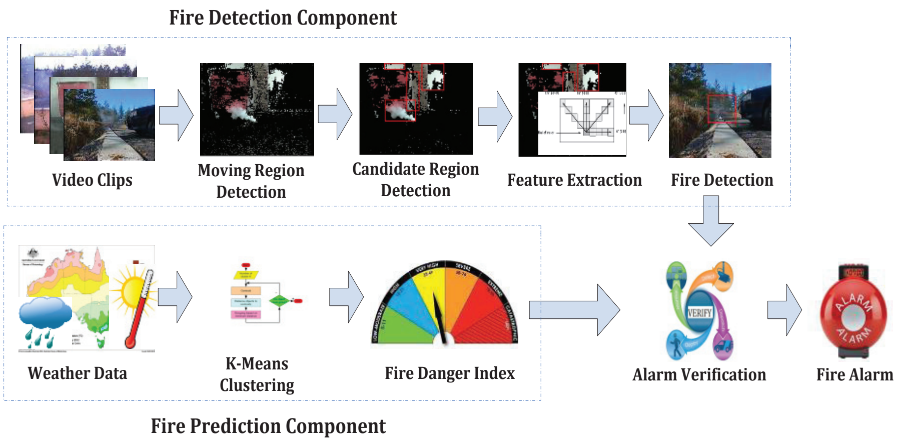


Figure 1: The proposed fire model for rural-urban interface area

leads to some false alarms while moving object detection techniques provide candidate regions together with other moving objects [16].

In order to (i) address high correlated weather parameters for prediction, (ii) reduce the other moving objects from being selected as candidate regions, and (iii) decrease the false alarm rate, this work proposes a fire model integrating prediction and detection. An experimental prototype of the model is being developed along with performance evaluation. The overall contributions are: (1) Investigating the competency of unsupervised clustering algorithms for fire prediction, (2) Utilizing a Rule based Enhance Suppressed Fuzzy C-Means (EnSFCM) algorithm with the consideration of moving features for candidate region selection and (3) Incorporating prediction and detection for minimizing false alarm rates.

This paper is organized as follows. Section II briefly overviews the proposed fire model. Section III introduces the proposed fire prediction algorithm and Section IV presents the proposed fire detection algorithm. In Section IV, an alarm verification technique is described. Experimental results and performance analysis are presented in Section V. Finally, Section VI presents conclusion and future work.

II. An Integrated Fire Model

The overall aim of this paper is to present fire prediction system using meteorological data along with robust methods for fire detection, and to describe an integrated model of prediction and detection. The proposed model has three components: fire prediction, fire detection and alarm verification. The fire prediction component gives fire danger index in order to predict fire on a scale of 1-5. Further, the fire detection component uses multi stage pattern recognition techniques in order to detect fire utilizing video based monitoring system. The alarm verification stage suppresses the false alarm rate utilizing the output of prediction and detection components. The main stages of the model are presented in Figure 1.

III. Fire Prediction Algorithm

The proposed fire prediction algorithm provides fire danger index on a scale of 1-5. Here 1 represents to the lowest fire risk that could occur on a specific day, 3 depict the moderate level, and 5 denote the highest fire risk. This prediction technique requires monitoring a number of weather parameters in a continuous basis during the days being used in the algorithm. These weather parameters are used as features for the prediction system. The computational effectiveness of this technique is derived from utilization of 3 weather parameters which are highly correlated with fire [17]. The selected features are: the maximum temperature of the day, the average humidity of the day, and the average rainfall of the day. These three parameters have significant impact on fire occurrence.

This study employs K-means algorithm which is a simple and effective unsupervised clustering algorithm [18]. K-means algorithm produces crisp and robust clusters. Robust and crisp cluster means that the clusters do not share any data points between them as well as they are well distant from each other's. Also it is computationally effective. For fire prediction system if high temperature becomes an outlier for a cluster containing lower humidity and rainfall, then a clustering algorithm without crisp clusters can show low fire danger index for this definite cluster; whereas in reality there is a high chance of fire ignition. In the same way, it can also happen when a weather parameter is being shared by the multiple clusters. That is the reason of choosing unsupervised K-means clustering algorithm for fire prediction system.

For a given set of weather parameters, $(w_1, w_2, \dots \dots w_n)$ this algorithm aims to minimize the objective function in order to classify the given data sets into k clusters where k is the number of defined clusters. The objective function is defined by

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| w_i - c_j \right\|^2 \qquad (1)$$

Where $\left\| w_i - c_j \right\|^2$ is the distance between a weather parameter, w_i and the cluster centroid, c_j. In weather data sets, highest range of temperatures is 45^0C whereas highest range of rainfall is nearly 92mm and humidity is approximately 100%. So for simplification, rainfall and humidity data sets are normalized before applying k-means. In this work, the number of clusters is selected to be the same as the number of fire risk levels. There is a high risk of fire when the temperature exceeds 35^0C and the relative humidity drops below 20%. Consequently, when the rainfall is less than 1mm, there is a high risk of fire. Depending on the danger levels of weather parameters, the k-means algorithm clusters the input weather data sets into five clusters. Further, for providing the fire danger index to the given cluster, this paper measured the distance between cluster centers and danger levels of the weather parameters. In this way, it provides fire danger index from the lowest value of 1 to the highest of 5 for the clusters. In Figure 2, 3D weather parameter space is shown here after applying k-means clustering algorithm.

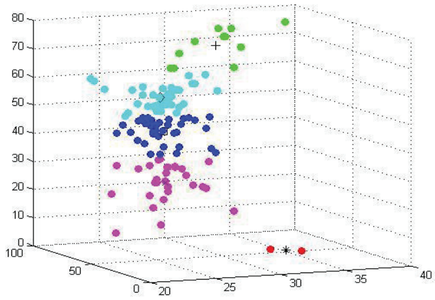


Figure 2: 3D weather parameter space for five clusters where cluster centers are marked

IV. Fire Detection Algorithm

The proposed video based fire detection algorithm focuses on video based smoke detection as smoke is the early sign of fire. A flowchart of the fire detection algorithm is shown in Figure 3.

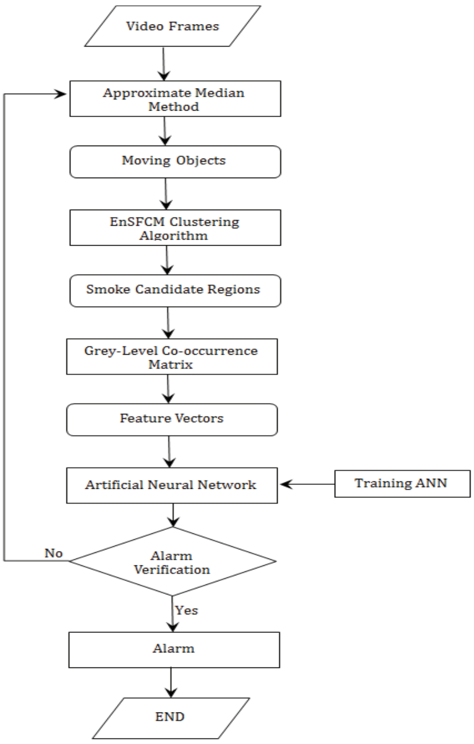


Figure 3: Flowchart of the proposed fire detection component using video

A. Moving Region Detection

Moving region detection is the fundamental part of video based detection. Smoke is a moving object that diffuses into the frames with a gradual change of size and color. This work exploits a simple and effective approximate median subtraction method that has been widely used in the literature due to its high accuracy and low computational complexity [19]. Approximate median subtraction method utilizes only the grey level images. It is a combination of frame differencing between moving blobs with background intensity and a predetermined threshold value [19]. Let $I_n(i,j)$ denotes the intensity value of the pixel. The projected background intensity value of the same location is calculated as follows:

$$B_{n+1}(i,j) = \begin{cases} B_{n+1}(i,j) + 1, & \text{if } I_n(i,j) > B_n(i,j) \\ B_{n+1}(i,j) - 1, & \text{if } I_n(i,j) < B_n(i,j) \end{cases} \quad (2)$$

where $B_n(i,j)$is the previous estimate of the background intensity value at the same position in the preceding frame. Using equation 2, background is updated after every frame. Primarily, the value of $B_1(i,j)$ is set to the intensity of $I_1(i,j)$. A pixel positioned at $(i,j)$is shifted if

$$|I_n(i,j) - B_n(i,j)| > T \quad (3)$$

Here T is the threshold value which is defined experimentally. The extracted moving regions include some small noise spots. So, a median filtering is applied on these extracted moving regions in order to eliminate these noise blobs and enhance the quality. However, the moving regions include both smoke and non-smoke regions. Therefore, a clustering algorithm will be required to extract smoke candidate regions.

B. Candidate Region Selection

Moving regions contain not only smoke but also other moving objects such as moving car, a walking person, etc. That's why it is essential to apply further analysis to detect the smoke candidate regions effectively. Therefore, this work utilized Rule based Enhanced Suppressed Fuzzy C-Mean (EnSFCM) clustering algorithm for detecting candidate smoke regions. EnSFCM considered color and moving features such as surface roughness and area of the moving regions. The reason for choosing EnSFCM is that it provides optimal suppression factor for the perfect clustering of the given data set with improved clustering accuracy and convergence speed [20]. In practice, smoke colors vary from bluish white to black which can be identified accurately by the chrominance and saturation attributes of color. Nguyen et al. claim that hue and saturation components of HSI color space are reliable for filtering the smoke candidate regions [15]. Pursuing this further, this work analyzed the H and S components of HSI color space for EnSFCM clustering algorithms to cluster the smoke candidate regions.

Let $X = \{x_1, x_2, \ldots \ldots x_n\}$ where *n* is the number of image pixels. The EnSFCM algorithm sorts the data set *X* into *c* clusters. The standard objective function is defined as follows:

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{n} \mu_{ik}^m d^2(x_k, v_i) \quad (4)$$

where $d^2(x_k, v_i)$ is the Euclidian distance between the data point x_k and the centroid v_i of the *i*th cluster and μ_{ik} is the membership function of the data x_k to the kth cluster. Membership function is defined as a mathematical function to grade the association of a data to a cluster. The parameter m, which is called the fuzzy factor, controls the fuzziness of the resulting partition, ($m \geq 1$), and c is the total number of clusters. EnSFCM clustering is an iteration-based clustering technique that produces an optimal number of c classes by minimizing the objective function J_m with updated values of μ_{ik} and v_i according to the following equations:

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{d^2(x_k,v_i)}{d^2(x_k,v_j)}\right)^{1/(m-1)}\right]^{-1} \quad (5)$$

$$v_i = \frac{\sum_{k=1}^{n} \mu_{ik}^{m} x_k}{\sum_{k=1}^{n} \mu_{ik}^{m}} \quad (6)$$

EnSFCM modifies the membership function by utilizing the suppression factor as follows:

$$\mu_{pk} = 1 - \alpha + \alpha\mu_{pk} \text{ and } \mu_{ik} = \alpha\mu_{ik} for\ i \neq p \quad (7)$$

where μ_{pk} refers to data point, x_k belongs to the largest cluster p, and α is the suppression factor which ranges in the interval [0,1] which should be prior given according to the Suppressed Fuzzy C-Means (SFCM) algorithm. EnSFCM then updates the value of v_i with the new membership function. The pixel clustering iterations are terminated when the termination measurement is satisfied.

To match the perfect clustering of the given data set, it is necessary to select an optimal suppression factor. In addition, selection of the suppression factor is related to robust cluster. Therefore, a new exponential function is defined to select the optimal suppression factor, and it is automatically updated at each iteration:

$$\alpha = exp\left(-\min_{i \neq j} \frac{\|v_i - v_j\|^2}{m}\right) \quad (8)$$

where v_i is the centroid of the ith cluster, v_j is the centroid of the jth cluster, and m is the fuzzy factor. Both the fuzzification parameter and the suppression rate influence the clustering rate of the algorithms. Thus we intuitively selected $\frac{\|v_i - v_j\|^2}{m}$, illustrating the separation strength between the clusters and the fuzzy factor that signifies the fuzziness of the values for the clustered data points.

In order to select the perfect cluster with smoke candidate regions, we used definite rule comprised of following three steps:

Step 1: Hue of cluster centroid lies within a predefined threshold

Step 2: Saturation of cluster centroid should be within the range of predefined saturation threshold

Step3: If (Step 1) AND (Step 2) are true for definite centroid, then the cluster is smoke, otherwise it is non-smoke. It means that when cluster centroid satisfies the hue and saturation threshold, then the cluster is selected for next processing. If it is not satisfied, then it can be determined that the objects in the video are non-smoking moving objects.

Figure 4 illustrates the output of candidate region selection. In Figure 4(a), screenshot of the original video frames is shown and moving regions using approximate median subtraction method is presented in Figure 4(b). The extracted candidate regions by EnSFCM are shown in Figure 4(c). However this stage can detect both smoke and smoke-like areas. Next, smoke features will need to be extracted.

(a) (b) (c)

Figure 4: (a) Representative frame of the input video. (b) Moving regions of the video. (c) Candidate regions of the video using EnSFCM

C. Feature Extraction

The extracted candidate regions can consist of smoke and smoke-like colored moving objects. These smoke-like colored objects produce false alarms as well as lead to missed detection. In order to decrease the false alarm and missed detection rates, investigation of features plays a critical role for distinguishing smoke from the smoke-like colored objects. Smoke regions normally have a higher intensity and frequency than the background and the other objects. Thus, to consider these characteristics of smoke, this paper applied Grey Level Co-occurrence Matrix (GLCM) in order to extract texture features from selected smoke candidate regions. Because texture features effectively distinguish the smoke regions from the non-smoke regions. GLCM considers the relationship of the grey levels between neighboring pixels of the original image. Experimentally we selected six most effective GLCM features for separating smoke from non-smoke objects. The features that have been used in this study are contrast, dissimilarity, homogeneity, difference variance, inverse difference normalized, and inverse difference moment normalized. These features are highly discriminative for detecting smoke from other moving objects.

D. Smoke Detection Using ANN

The machine learning algorithms will be used to decide whether it is smoke or not based on these effective features that are extracted from the candidate regions. In this study, Artificial Neural Network (ANN) is used to classify between smoke and non-smoke. The output of an ANN is being used to activate the alarm when smoke is identified based on the extracted feature vectors. Multiple layers are needed for ANN structure as there is a non-linear relationship between the input features and the output. Three layers of ANN are used where first two layers have six neurons and output layer has one neuron. The hyperbolic tangent sigmoid function is used as an activation function which is defined by

$$\mathrm{tansig(n)} = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \quad (9)$$

The output of ANN activates the alarm for detecting the presence of smoke utilizing the extracted features.

Movie 1 **Movie 2** **Movie 3** **Movie 4** **Movie 5** **Movie 6** **Movie 7**

Figure 5: Screenshot of the videos used for this study. Movie 1 –5: positive videos and Movie 6 –7: negative video

V. ALARM VERIFICATION TECHNIQUE

A method of verifying alarm is incorporated in this proposed fire model. If a possible fire event is sensed by the detection component, then before activating the alarm the system checks the fire danger risk for the area under monitoring. In this situation if the risk level is below the moderate value, the detection component checks the whole process for evaluating detection and suppresses the false alarm when needed. This help to decrease the false alarm rate of the model. Whereas when the fire danger risk is above the moderate level, the system takes the situation as a danger one and triggers the alarm immediately.

VI. EXPERIMENTAL ANALYSIS

MATLAB environment was used to build and test our detection and prediction algorithms. The weather data is collected from the Bureau of Meteorology for the year 2014. Real data sets of smoke and non-smoke videos are used from databases which are also extensively used in the literature [16]. We selected five standard positive videos with smoke and two negative videos with smoke like color objects. The frames of the videos are given in Figure 5. The resolution of the videos used is 320×240 pixels. In order to train ANN, 800 fire samples and 800 non-fire samples were used respectively. In this work, regions of interest in the video frames were used as samples for training purpose. The training movies include outdoor fire and smoke, bushfire, indoor fire and smoke, non-fire and moving objects which exhibit the same color as fire and smoke. To evaluate the performance of the proposed algorithms, we set some empirical parameters. For EnSFCM, we selected degree of fuzzification (m) = 2 and the termination threshold (ε) = 0.0001. The threshold values have been chosen experimentally. After clustering by EnSFCM, the centroid values for the hue and saturation components have been plotted. From the graph, it is concluded that the hue range of smoke is 0 – 0.26 and saturation threshold is 0.8. Also threshold for approximate median subtraction method is 4 which are also selected experimentally.

The performance of the prediction and detection algorithms of the proposed fire model was evaluated separately. For prediction system fire danger index is provided for five classes depending on the centroids values of temperature, rainfall and humidity as shown in Figure 6. In Figure 6, it is evident that fire danger index is correctly assigned to the classes depending on the values of input parameters. Highest fire danger index is given for class 4 as there is high chance of fire ignition. For class 4, almost no rainfall is recorded with nearly 25% relative humidity and temperature of about 40 degree Celsius. These ranges of weather parameters have greater effects on fire ignition. In the same way lowest fire danger index is set for class 1 as a significant amount of rainfall is calculated for this class. In the same way fire danger index is provided according to the other clusters. After classification, the performance is evaluated calculating accuracy of the each class using confusion matrix which is shown in Table 1. The equation for calculating accuracy is given below:

$$Accuracy = \frac{TP+TN}{Total\ Population} \tag{10}$$

Here TP represents the number of data correctly assigned to classes and TN represents the number of data falsely allocated to classes. The average accuracy of 94.2% shows the ability of the algorithm to correctly predict the fire hazards.

Table 1: Accuracy of Fire Prediction Algorithm

Classes	Accuracy (%)	Mean Accuracy	Standard Deviation
1	100	94.92	4.92
2	90.9		
3	89.6		
4	94.1		
5	100		

The accuracy of the fire detection component is checked by calculating percentage of true positive (PTP), percentage of false positive (PFP), and percentage of false negative (PFN). PTP measures the number of correctly detected smoke as a smoke while PFP is the percentage of incorrectly identified smoke as a non-smoke. In addition, PFN measures the rate of identifying non- smoke objects as a smoke. When the PFN value is lower, it represents the better performance.

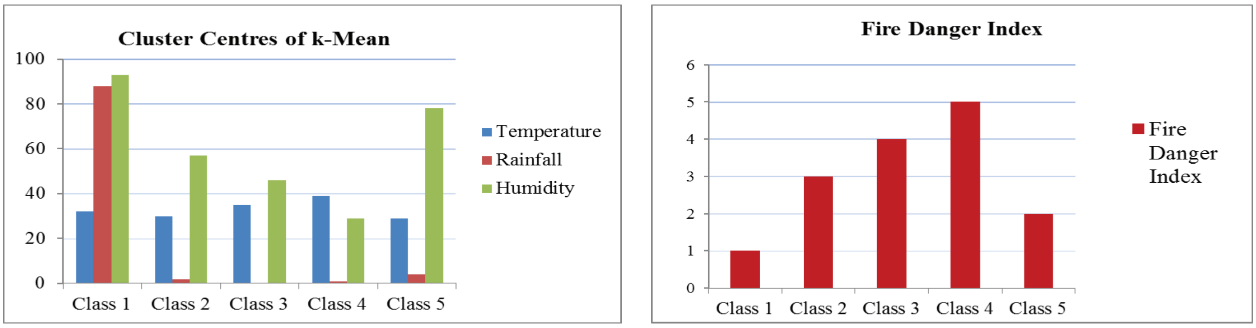
The performance of the video based fire detection part of the model is compared with other state-of-the-art algorithms using same video sequences: Algorithm 1: fast accumulative motion orientation model [21]; Algorithm 2: four stage smoke detection algorithm [14]; Algorithm 3: multistage optical smoke detection [15]. Testing videos include single smoke event depicting rural-urban interface area. Table 2 represents the overall comparison rate for positive smoke videos and Table 3 represents for negative videos. PTP, PFP and PFN are calculated for sequence of frames in the video clips as the proposed algorithm considered moving features. The proposed video based fire detection outperformed the other three state-of-the-art algorithms in terms of PTP and PFP as shown in Table 2.

In case of first three movies, the proposed algorithm achieved average 99.7% accuracy as smoke is quite significant in the video frames. For Movie 4, smoke is almost same color like the background as well as almost invisible amount of smoke in the video that lead to the reduced accuracy of 93.3%. The overall results show significant performance improvement compared to the most of the existing techniques of interest by achieving average accuracy of 97%.

In addition, Wilcoxon signed-rank test is utilized in order to check the statistical validity of the proposed video based detection system. Wilcoxon signed rank test does not require any assumptions about the distribution. In addition, outliers cannot affect the Wilcoxon test statistic which makes it more sensible than the other paired statistical test methods [22]. It is a non-parametric statistical hypothesis test to evaluate the statistical significance of the performance of the proposed method. Wilcoxon signed-rank test compares the two related samples to check whether their population means differ. The test includes some basic steps for computing statistical significance [15, 22, 23].

1. For each input, compute the difference between two paired values.
2. Sign is denoted in the Sign Column by + or -. If both values are equal, then discard this value.
3. The data is ranked from the smallest value of 1 to the largest value. When two equal differences occur, then assign each equal value to the mean of the ranks.
4. Compute the Wilcoxon test statistic W. W+ is the sum of all the positive ranks and W- is the sum of all the negative ranks.
5. Finally, this test statistic is analysed using the critical value table provided for the Wilcoxon test. If the test statistic is less than or equal to the critical value, then the null hypothesis is rejected. It means that the difference between two algorithms is significant. Otherwise, null hypothesis is true when the test statistic is greater than the critical value.

In the Table 4 and Table 5, Wilcoxon signed-rank test results are shown between proposed algorithm (X) and two state-of-the-art algorithms (Y1 & Y2). For example, Wilcoxon signed rank test between the proposed algorithm (X) and Algorithm 1 (Y1) is shown in Table 4 where test statistic W+=15 and W-=0. According to the table of critical value for Wilcoxon signed rank test, here critical value is 2 for the test statistic W-=0 and n=5 data points. So the test statistic is less than the critical value which represents significant difference between two algorithms. Following this, the proposed algorithm is also statistically significant in comparison to other two conventional algorithms.



(a) (b)

Figure 6: (a) Cluster Centres of temperature, rainfall and humidity for five clusters and (b) Fire Danger Index based on the value of cluster centres

Table 2: Percentage of True Positive (PTP) and False Positive (PFP)

	Total No of Frames in the Video	Algorithm 1[21]		Algorithm 2[14]		Algorithm 3[15]		Proposed	
		PTP	PFP	PTP	PFP	PTP	PFP	PTP	PFP
Movie 1	165	85.5	14.5	92.7	7.3	100	0	99.1	0.9
Movie 2	140	87.1	12.9	91.4	8.6	100	0	100	0
Movie 3	900	88.4	11.6	94.5	5.1	99.3	0.7	100	0
Movie 4	190	82.6	17.4	85.8	14.2	91.5	8.5	93.3	6.7
Movie 5	214	82.7	17.3	88.3	11.7	91.7	8.3	92.8	7.2
Average	322	85.3	14.8	90.5	9.5	96.5	3.5	97.0	2.9

Table 3: Percentage of False Negative (PFN)

	No of Frames	Algorithm 1[21]	Algorithm 2[14]	Algorithm 3[15]	Proposed
Movie 6	92	0.6	0.4	0	0
Movie 7	160	2.9	4.3	0	0
Average	126	1.8	2.3	0	0

Table 4: Result of Wilcoxon Signed Rank Test for PTP between the proposed algorithm (X) and Algorithm1 (Y1)

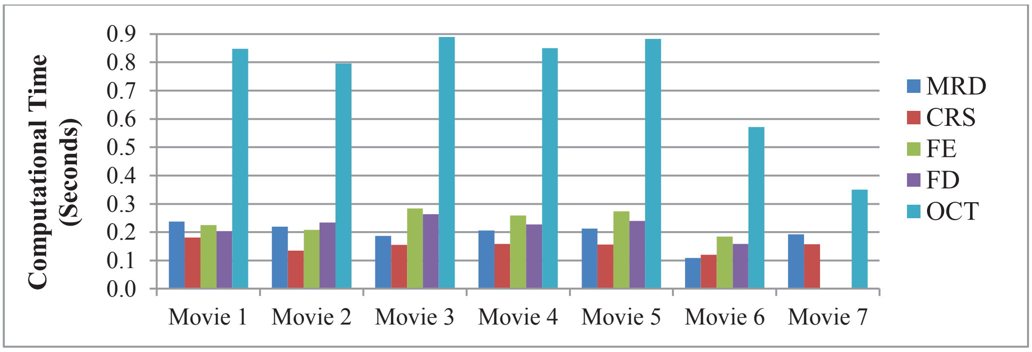
	Proposed (X)	Algorithm1 (Y1)	Sign	X-Y1	$\lvert X - Y1 \rvert$	Rank of $\lvert X - Y1 \rvert$	Signed Rank
Movie 1	99.1	85.5	+	13.6	13.6	5	5
Movie 2	100	87.1	+	12.9	12.9	4	4
Movie 3	100	88.4	+	11.6	11.6	3	3
Movie 4	93.3	82.6	+	10.7	10.7	2	2
Movie 5	92.8	82.7	+	10.7	10.1	1	1

Note: The Wilcoxon test statistic, W_+ = 5+4+3+2+1=15 and W_-=0

Table 5: Result of Wilcoxon Signed Rank Test for PTP between the proposed algorithm (X) and Algorithm2 (Y2)

	Proposed (X)	Algorithm2 (Y2)	Sign	X-Y2	$\lvert X - Y2 \rvert$	Rank of $\lvert X - Y2 \rvert$	Signed Rank
Movie 1	99.1	92.7	+	6.4	6.4	3	3
Movie 2	100	91.4	+	8.6	8.6	5	5
Movie 3	100	94.5	+	5.5	5.5	2	2
Movie 4	93.3	85.8	+	7.5	7.5	4	4
Movie 5	92.8	88.3	+	4.5	4.5	1	1

Note: The Wilcoxon test statistic, W_+ = 3+5+2+4+1=15 and W_-=0



	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
No of Frames	165	140	900	190	214	92	160
OCT (seconds)	0.8474	0.7956	0.8900	0.8499	0.8831	0.5718	0.3492

Figure 7: Computational Time of the proposed fire detection approach for both positive and negative videos

In this part, the computational time of the video based fire detection system is provided. Since fire detection requires immediate action to avoid destruction, the time complexity of fire detection algorithm plays a vital role for real-time applications. Computational complexity of an algorithm can be calculated as the execution time of the algorithm. In this work, computational time for the proposed fire detection technique is computed for both positive and negative videos. As the proposed approach comprised of four steps, computation time is measured for each step as well as for the overall procedure. Figure 7 shows the computational time for the proposed fire detection approach for the experimental video samples. Here, MRD represents the Moving Region Detection, CRS means Candidate Region Selection, FE for Feature Extraction, FD stands for Fire Detection and OCT represents the Overall Computational Time for the whole detection process. The time complexity has been measured in the computer environment using MATLAB simulation software. From Figure 7, it is evident that CRS takes a relatively time compute due to the utilization of fast EnSFCM algorithm. It is also apparent from the figure that FE and FD steps take zero time for Movie 7. This movie contains smoke colored moving objects which are not detected as smoke candidate regions by EnSFCM. It is because EnSFCM considers not only color features but also moving features. Though the proposed approach does not meet the real time application requirements, it can be improved using NVIDIA, Graphics Processing Unit (GPU), and Digital Signal Processors (TI DSPs). In future, we will work on reducing the computational time while maintaining the accuracy of the proposed technique.

VII. Conclusion

This paper proposed an integrated fire prediction and detection model for rural-urban interface areas. Prediction information helps people to avoid fire hazards and also it can assist in controlling fire propagation. Further, early fire detection helps to save disastrous damages of lives and properties as well as to avoid greater effects on environment. This model comprised of fire prediction, video based fire detection, and alarm verification. The alarm verification stage utilizes outputs of prediction and detection system to decrease the false alarm rate of the system. Performance evaluation focused on testing the model's fire prediction and detection algorithms separately in order to demonstrate their contribution in the overall model. The results of testing on videos depicting rural-urban interface areas demonstrate that the proposed model has potential to be applied for fire prevention in these areas. This study leads to the development of new ideas in field of fire monitoring and detection. In the future, we will focus on continuing the development of the fire prediction system and exploring an efficient ways of combining both image and video with weather data. Investigation will also focus on minimizing false alarm rate along with missed detection rates.

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