DESIGN AND DEVELOPMENT OF FOREST FIRE MANAGEMENT SYSTEM

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ABSTRACT

Forest fire is one of those natural disasters that have been causing huge destruction in terms of loss of vegetation, animals and hence affects the economy. Image segmentation techniques have been applied on satellite images of forest fire to extract fire object and some data mining techniques have been used for predicting the spread of forest fire. This paper proposes a novel approach to isolation of fire region using time-sequenced images, classifying fire images from non-fire images, predicting its movement and estimating the area burnt. Once the images are enhanced, the fire region is segmented out. Feature extraction provides the necessary inputs for classification of images as fire and non-fire images. Linear regression is used to predict the movement of forest fire to facilitate better evacuation strategy. Burnt area is calculated from the difference image. This work is helpful in drafting evacuation strategies quickly by predicting the movement of forest fire and facilitates the kick-off of rehabilitation activities by identifying and assessing the burnt area.

KEYWORDS

Forest fire management, Image segmentation, Classification, Forest fire movement prediction, Burnt area calculation

1. INTRODUCTION

Forest fire poses a huge challenge to the human community by destroying vegetation and animals on a large scale within a short span of time. Forest fires are generally started by lightning, but also by human negligence, and can burn thousands of square kilometers. Forest fires are caused by the drying out of branches and leaves, and therefore become highly flammable. Satellite images provide sufficient amount of forest fire images in frequent intervals.

With the advancement in remote sensing technologies, satellites are able to facilitate study of fire dynamics along with capturing of weather data. Meteosat Second Generation satellites observe the earth continuously and send images including those of forest fires to the ground station [1]. Spatial image mining of these images can help us understand forest fire better and predict its behavior.

Image Mining is focused on extracting patterns, implicit knowledge, image data relationship or patterns which are not explicitly found in the images from databases or collections of images. Some of the methods used to gather knowledge are: image retrieval, data mining, image processing and artificial intelligence [2]. The satellite images help us find out the hotspots caused by forest fire [3].

1.1. Review of literature

Preprocessing of satellite images prior to image segmentation is essential. Images may have noise which can be detected and removed during the preprocessing step. Also, by enhancing edges of the input images, the dynamic range of chosen features is reduced.

Region-based segmentation extracts a specific region from an image based on an initial seed. This method examines neighboring pixels of initial “seed points” and determines whether the pixel neighbors should be added to the region. The process is iterated on until the region of interest is extracted. From the segmented region, features are extracted and used for classification.

The features of the segmented region (Average Intensity of the image, Average pixel range, Number of white pixels in segmented image, green plane average, Entropy, NDVI – Normalized Difference Vegetation Index) are extracted and used for classification.

Classification refers to an algorithmic procedure for assigning a given piece of input data into one of a given number of categories or classes. It involves grouping data into classes based on some measure of inherent similarity [4]. In spatial classification, the attributes of the neighboring objects also influence the class membership. Hence, neighborhood factor needs to be included in our calculations for classification. In classification, the users first define the classes and provide a training set which includes the input data along with the classes associated with it. Based on the training set, the classification rules are inferred [5]. These rules are applied on the test dataset. K-nearest neighbor (KNN) is used in this work.

To evaluate the classification accuracy, a standard method called confusion matrix is used in remote sensing. It contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. Each time the user gives a new positive or negative training example, the posterior probabilities are updated [6].

With the combination of statistics and image processing techniques, it is possible to predict the direction of the forest fire movement. Linear regression helps to do the prediction. The variables used for prediction are time, location, spread, intensity, NDVI, wind direction and wind speed. This prediction will help the fire managers to take necessary actions to prevent the further spread and loss.

To assess the fire affected area, the pre- and post-disaster images of the same location are needed. Image differencing is a process of subtracting two different timed images of the same location pixel by pixel to create the difference image [7]. After finding the fire affected region, it is possible to find out the total area from it. The assessment of the burnt region gives the approximate loss. This will help the forest department to do the necessary plan for rehabilitation work like reseeding the vegetation in the fire affected area.

2. Proposed Architecture

In this paper, a combination of two systems - Segmentation and Classification system and Prediction and Assessment System - is proposed. The architecture is presented in figure 1. The segmentation and classification system consists of region based segmentation, feature extraction and classification of images. Region based segmentation segments the forest fire objects to identify whether a particular image has the fire affected area or not. Relevant features are extracted from the fire objects to help in classification. Then, the fire and non-fire images are classified based on the features extracted. The prediction and assessment system predicts the movement of forest fire to help quicker evacuation decisions and calculates the burnt area for facilitating rehabilitation efforts.

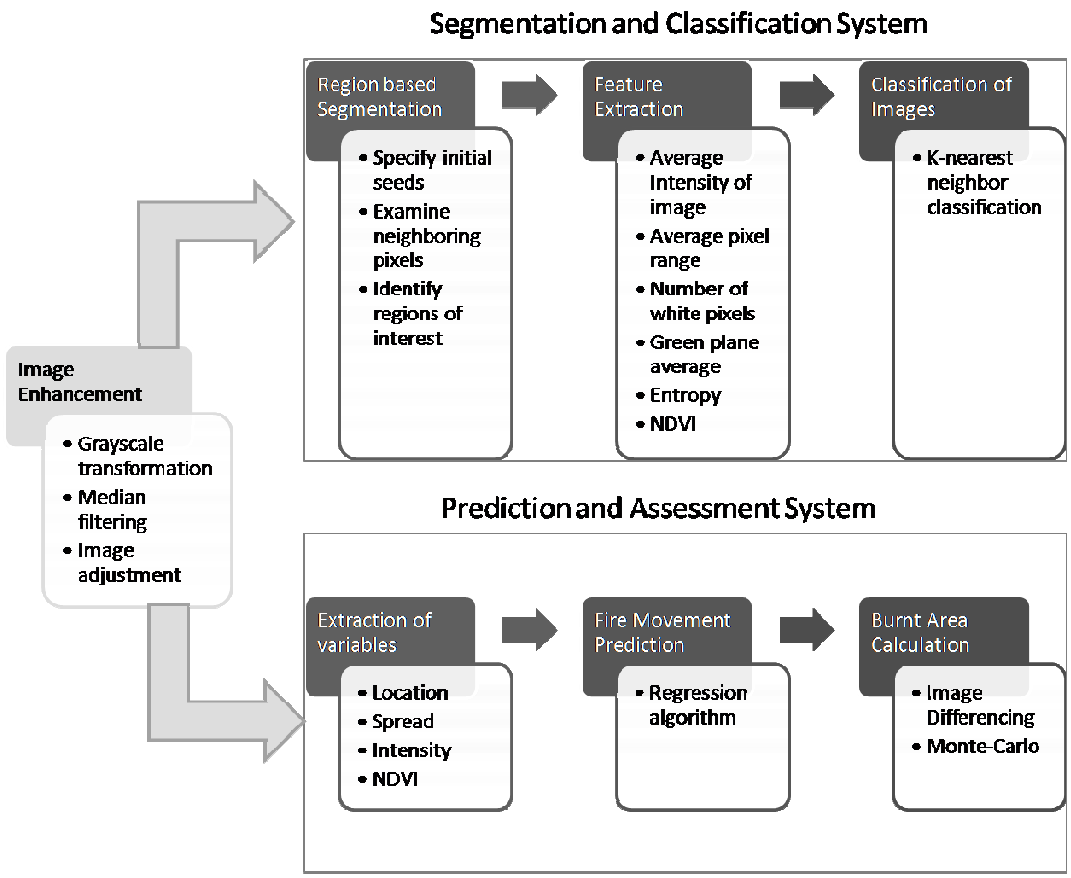

Figure 1. System architecture

Before doing the segmentation, the images should be enhanced to get better segmentation results. Image enhancement refers to accentuation or sharpening of image features such as edged, boundaries or contrast to make it more useful for analysis and display. This process does not increase the information content in the data but only increases the dynamic range of the chosen features so that they can be detected easily [8]. Image enhancement includes contrast manipulation, noise reduction, edge sharpening, filtering, pseudocoloring and so on. In this work, image enhancement enables easy extraction of fire objects.

K-nearest neighbor algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. In the classification phase, k is a user-defined constant denoting the number of clusters present in the data, and an unlabelled sample is classified by assigning the label which is most frequent among the k training samples nearest to it. Euclidean distance is used as the distance metric [9]. Once the instances are placed in the appropriate clusters, the cluster centers are recalculated. Instance classification and cluster center computation are done in iterations until the cluster centers stabilize. In instance based training, the class of unknown sample is predicted based on the nearest training instance [10]. Forest fire affected areas are typically ash colored and a sample image (Figure2) depicts the affected area.

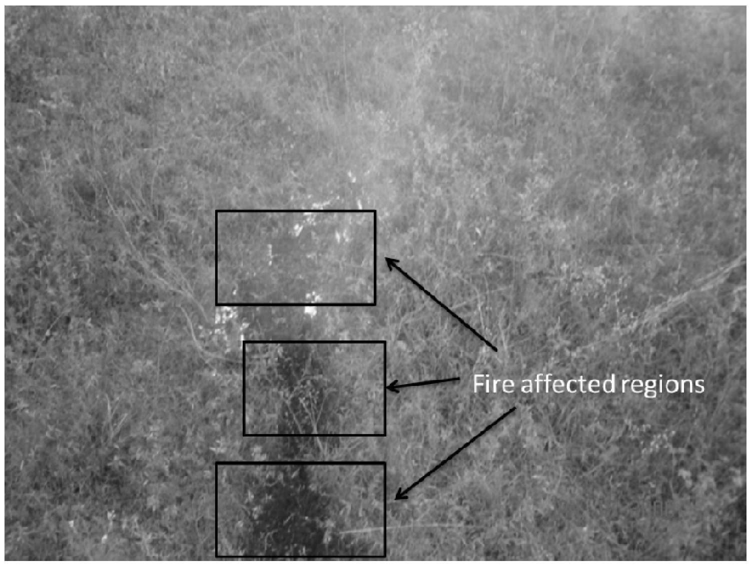

Figure 2. Fire affected area

2.1. Preprocessing of forest fire images

The images used in this work are simulated and captured in real time manner. The study area of the forest is manually fired and the images were shot in ten seconds interval. Hundred images of 640x480 resolution have been captured and used in this work.

Median filter is used to remove the outliers (noise) while maintaining the sharpness of the image. Image adjustment is done on the noise-removed image to increase the contrast of the image. The various steps involved are:

i. Read the satellite images

ii. Convert into grayscale images

iii. Check for speckle noises

iv. Apply two dimensional median filter

v. Check whether the satellite images lack contrast

vi. Apply contrast stretching technique to enhance the image

Figure 3 depicts the images at each stage of preprocessing along with their intensity profiles.

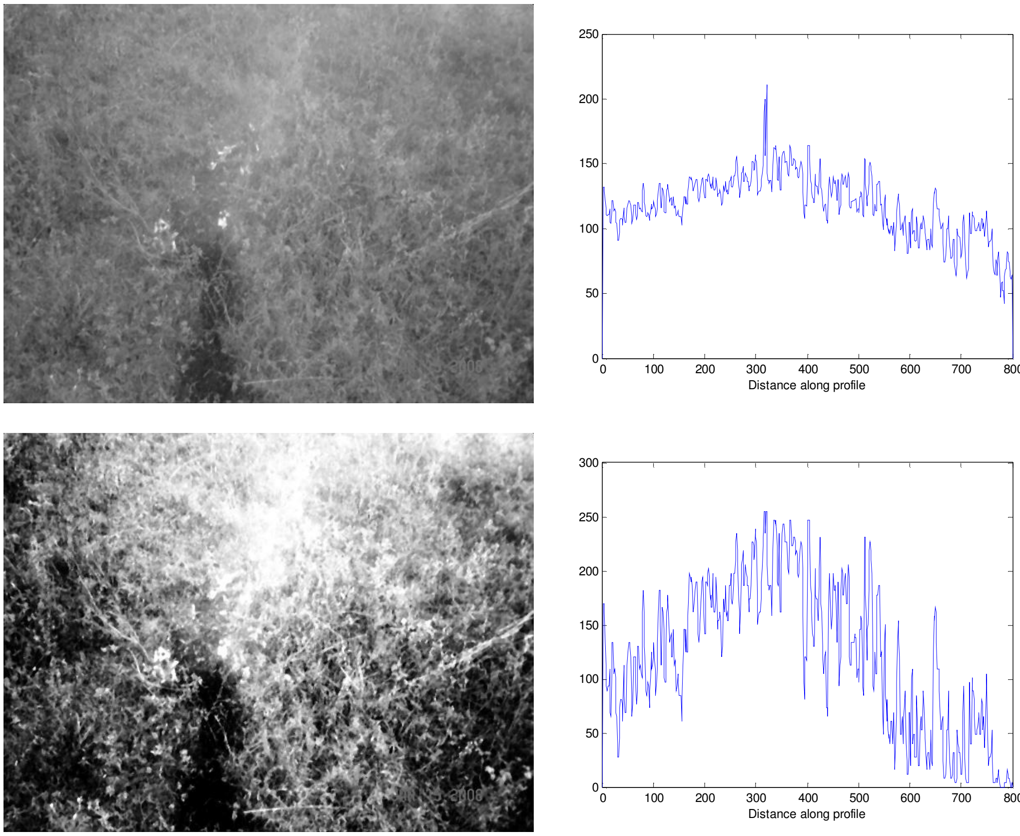

Figure 3. Top row - Filtered image and its intensity profile, Bottom row – Contrast enhanced image and its intensity profile

2.2. Image Segmentation

The forest fire region is extracted out of the images using region growing algorithm. The basic formulation of the region-growing algorithm is:

1) The addition of all sub-regions produces the entire image region

2) Every sub-region must be connected with other region, which means there is no isolated region

3) The intersection of two different regions always provides a NULL value, which means there regions must be disjoint

4) The predicate of all the sub-regions must be true

5) The predicate of two regions are different

Region growing algorithm works as follows: It starts with selecting a seed. Seed value can be a specific gray level or color information. In this work, gray level (255) is used as seed. Fire pixels are depicted as white pixels and hence this seed value is selected. After identifying the seed, the neighboring pixels are examined to look for same characteristics. Such pixels are grouped into a region. The growth continues iteratively until there is no more pixels to be grouped into the region. A sample segmented image highlighting the fire object is shown in figure 4.

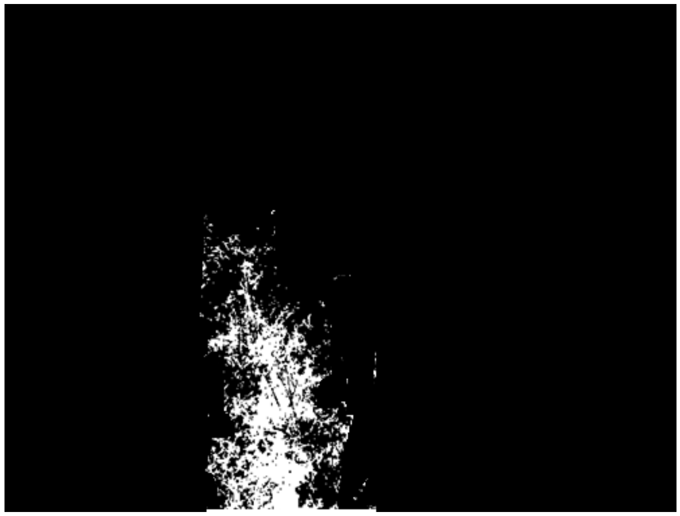

Figure 4. Segmented image

2.3. Feature Extraction

In order to proceed with classification, the features need to be extracted from the images. The selected features are stored in an array for further processing. The features should uniquely identify the image and should have lesser dimensionality to reduce the computational time of the subsequent steps.

The following features are extracted from the set of fire and non-fire images:

i. Average Intensity of the image (avg_i)

ii. Average pixel range (avg_pix_range)

iii. Number of white pixels in segmented image (white_pix)

iv. The green plane average (green_plane_avg) from original image

v. Entropy

vi. NDVI – Normalized Difference Vegetation Index

Table 1 shows extracted feature set for forest fire images.

Table 1. Sample features extracted from forest fire images

Image	Avg_i	Avg_pix_range	White_pix	Green_plane_avg	entropy	NDVI	Class
Img1	142.3986	90	2282	80.247	6.329	0.2822	Fire
Img2	110.139	80	5183	86.2305	6.1932	0.271	Fire
Img3	171.8275	125	2803	115.7552	6.0759	0.314	Fire
Img4	114.6921	75	3157	65.1263	6.3928	0.3012	Fire
Img5	82.0199	110	3418	68.9521	6.9123	0.2621	Fire
Img6	122.4886	100	5355	71.9144	6.7136	0.281	Fire
Img7	110.1312	90	5185	86.2286	6.1936	0.31	Fire
Img8	86.1123	80	4128	69.3686	6.6611	0.308	Fire
Img9	110.1294	85	5178	86.228	6.1937	0.252	Fire
Img10	119.3577	75	2703	72.2676	6.1597	0.2802	Fire
Img11	84.8903	82	0	86.088	6.2579	0	Nonfire
Img12	82.5026	80	0	88.8006	6.1247	0	Nonfire
Img13	79.9604	40	280	94.2923	7.1543	0.11	Nonfire
Img14	102.7115	60	1517	114.8943	7.4993	0.1772	Nonfire
Img15	34.8521	30	227	49.0992	5.2054	0.023	Nonfire
Img16	115.2215	60	14	128.1115	7.2118	0.0012	Nonfire
Img17	94.9123	90	0	101.9464	5.7189	0	Nonfire
Img18	121.1446	105	4227	124.6954	6.7622	0.198	Nonfire
Img19	55.7109	20	639	59.757	6.9749	0.16	Nonfire
Img20	84.5778	80	4016	96.8306	6.8563	0.167	Nonfire

2.4. k-Nearest Neighbor Classification

Once the feature set is extracted, the classifier is trained with a labelled feature set in which the class of every feature set is provided. The feature set is d-dimensional meaning that the features are in a d-dimensional space where d is the number of attributes. Here fire and non-fire are the two classes used.

Once the system is trained, it can identify a new test data. Based on the number of nearest neighbors, the test data is classified. Ties between classes are arbitrarily broken.

The steps for classification are as given below:

i. Training: The feature set that has all the samples is given to the system

ii. Choose a value for k

iii. Give the number of classes

iv. Input the test feature set

v. Find the distance between test set with the classes

vi. Classify the test set based on the k nearest neighbors

Here k=3. Hence based on 3 nearest neighbors, the class of the test sample is decided. Table 2 shows the results of KNN method.

Table 2. K-nearest neighbor classification

Row	**Predicted class**	**Actual class**	**Prob. For fire**	**Actual # of nearest neighbors**
1	Fire	Fire	1	3
2	Fire	Fire	1	3
3	Fire	Fire	1	3
4	Fire	Fire	1	3
5	Fire	Fire	1	3
6	Fire	Fire	1	3
7	Fire	Fire	1	3
8	Fire	Fire	1	3
9	Fire	Fire	1	3
10	Fire	Fire	1	3
11	Nonfire	Nonfire	1	3
12	Nonfire	Nonfire	1	3
13	Nonfire	Nonfire	1	3

Row	Predicted class	Actual class	Prob. For fire	Actual # of nearest neighbors
14	Fire	Nonfire	1	3
15	Nonfire	Nonfire	1	3
16	Nonfire	Nonfire	1	3
17	Nonfire	Nonfire	1	3
18	Fire	Nonfire	1	3
19	Nonfire	Nonfire	1	3
20	Nonfire	Nonfire	1	3

K value can be varied to get better results. Using k values as 1 or 2 will lead to misclassification. It was observed that above k=5, the number of errors stays at 6.

2.5. Fire movement prediction

First the high intensity location of fire (x,y) is identified. If there is dense vegetation, then it is more likely that fire will move in that direction. The spread of fire in x and y directions along with the intensity is also identified. Normalized Difference Vegetation Index (NDVI) is calculated. Wind direction and wind speed are also noted. Table 3 shows a sample list of the variable values extracted for regression.

Table 3. Extracted values for regression

X	Y	SIG X	SIG Y	I	WD	WS	NDVI
280	465	230	453	242	170	7.0	0.28
204	448	226	435	248	165	7.3	0.31
197	433	224	423	236	172	7.5	0.27
201	419	226	409	247	175	7.4	0.29
198	405	214	395	242	171	7.3	0.26
203	385	219	378	246	178	7.1	0.29
221	375	235	369	235	173	7.2	0.28
227	368	241	363	249	169	7.4	0.31
232	361	243	354	251	170	7.6	0.31

X	**Y**	**SIG X**	**SIG Y**	**I**	**WD**	**WS**	**NDVI**
234	353	247	346	244	173	7.3	0.28

The movement of forest fire can be done by applying linear regression analysis on these variables as given below:

$x_{t+4} \sim \alpha_0 + \alpha_1 x_t + \alpha_2 \sigma_{x,t} + \sigma_3 I_t + \sigma_4 WD_t + \sigma_5 WS_t + \sigma_6 NDVI$

$y_{t+4} \sim \beta_0 + \beta_1 x_t + \beta_2 \sigma_{x,t} + \beta_3 I_t + \beta_4 WD_t + \beta_5 WS_t + \beta_6 NDVI$

where α and β are calculated from the data, I is the intensity, σ is the spread in x and y directions.

2.6. Burnt area calculation

Burnt region is identified by image differencing technique which uses the difference of images taken before the fire and after the fire. The result of image differencing gives the burnt forest region. The identified region gives an idea about the loss of vegetation and animals that lived in that area. After finding the burnt region, the total loss can be calculated. Burnt area calculation is done by Poly area function provided by MATLAB. The burnt area is represented as a set of vertices stored in vectors X and Y. Passing these to Polyarea(X,Y) function of MATLAB, the burnt area is returned. Burnt area is calculated in terms of number of pixels.

Figures 5 and 6 depict the Pre-disaster and Post-disaster images respectively. It is clear that the pre-disaster image does not have any fire indications while the post disaster image has the burnt area and fire indications.

Figure 5. Pre-disaster image

Figure 6. Post-disaster image

The identified burnt region by using image differencing is shown in figure 7.

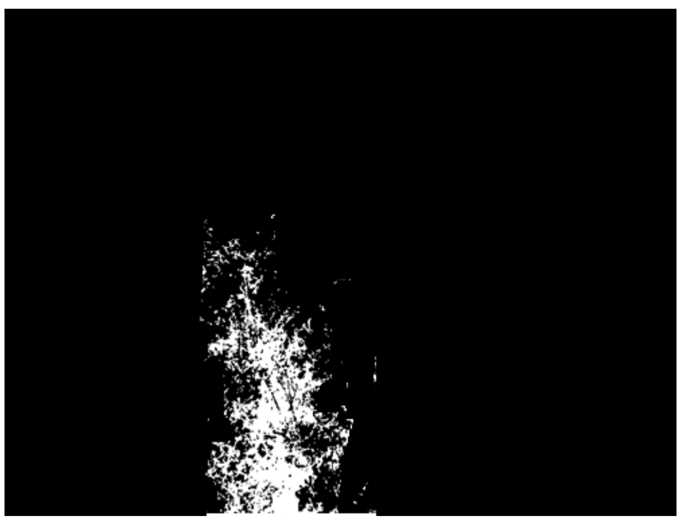

Figure 7. Identified burnt region

3. RESULTS AND DISCUSSIONS

3.1 Dataset used

A set of 100 (50 fire and 50 non-fire) images is considered for classification purpose. The images are JPEG images with a standard resolution of 640x480. The images and the features are stored in MySQL database. Extracted features include average intensity of the image, mean of all pixels, number of white pixels, average value of green plane, entropy and NDVI.

A set of 20 time-sequenced images is considered for prediction. The variables considered for prediction include location, spread, intensity, wind speed, wind direction and NDVI.

3.2 K-nearest neighbor classification

K value is set as 3. The extracted feature set is used for training. The classes in the training set are shown in table 4.

Table 4. Classes in training data

No. of Class	2
Class 1	Fire
Class 2	Non-fire

The probability of success is calculated for every tuple. Here, 3 nearest neighbors are considered. The confusion matrix for KNN classification is shown in table 5.

Table 5. KNN Classification – Confusion matrix

Classification confusion matrix		
	Predicted Class	
Actual class	Fire	Non-fire
Fire	50	0
Non-fire	2	48

Out of the 100 images taken, all the fire samples were classified correctly but 2 non-fire images were misclassified as fire images. This was due to cloud interpretation of non-fire image. % error was calculated and table 6 lists this data.

Table 6. Error report of k-nearest neighbor classification

Error Report			
Class	**No. of cases**	**No. of Errors**	**%Error**
Fire	50	0	0.00

Non-fire	50	2	4.00
Overall	100	2	2.00

Accuracy calculation for KNN is calculated by identifying the number of misclassifications. The table 7 shows the accuracy calculations for KNN.

Table 7. KNN Classification – Accuracy calculation

Total no. of images taken: 100		
Class	True classification	False classification
Fire	50 (TP)	0 (FP)
Non-fire	48 (TN)	2 (FN)

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} = 98/100 = 0.98 = 98\%$$

3.3 Forest fire movement prediction

Prediction is done by regression algorithm. Initially, the regression algorithm finds the coefficient values. Then, by using the regression equation, the fire movement direction is predicted.

Table 8 shows the predicted direction. The current value in the table shows the actual location of the forest fire. The predicted value shows the next fire movement location in a certain time interval. Based on the predicted direction of forest fire movement, the fire fighters can move their resources.

Table 8. Predicted forest fire movement

Row	**x-axis**			**y-axis**		
	Predicted value	**Current value**	**Residual**	**Predicted value**	**Current value**	**Residual**
1	223.7829021	280	56.21709789	461.7380501	465	3.261949936
2	207.4202112	204	-3.42021122	445.3256581	448	2.674341901
3	210.6747962	197	-13.6747962	433.1966163	433	-0.19661625
4	215.4495014	201	-14.4495014	417.6810101	419	1.318989909
5	211.7962699	198	-13.7962699	40.7229581	405	-0.72295808
6	213.9468891	203	-10.9468891	383.4197075	385	1.580292531

7	221.5452448	221	-0.54524475	375.4020998	375	-0.42809977
8	221.6208616	227	5.379138354	371.6275453	368	-3.62754529
9	222.0492577	232	9.950742324	363.5926829	361	-2.59268286
10	237.0876243	234	-3.08762427	354.071155	353	-1.071155

3.4 Burnt Area Assessment

The burnt area is identified by image differencing. This gives the burnt region of the forest as resultant. Then, the total lost area can be calculated. In this work, the burnt area is calculated as 29583.8777 pixels.

4. CONCLUSIONS

In this work, a novel approach to find forest fire and classify fire/non-fire images, predict fire movement and assess burnt area. This work can help fire fighters to take necessary action to control the spread of the fire as well as trigger off evacuation from the region. This also supports assessment of the burnt area after the disaster so that rehabilitation activities can be initiated immediately.

The overview of the experiments conducted and the summary of the results obtained are highlighted below:

- A set of 100 (50 fire and 50 non-fire) images is considered for classification purpose. Features used for classification include average intensity of the image, mean of all pixels, number of white pixels, average value of green plane, entropy and NDVI.

- Classification of these images produced 98% accurate results. The misclassification was due to non-fire images wrongly classified as fire images.

- A set of 20 time-sequenced images is considered for prediction. The variables considered for prediction include location, spread, intensity, wind speed, wind direction and NDVI.

- Prediction results show a misprediction of 1%-7% in most of the cases with a maximum of 20% in one of the cases.

As an extension to this work, this system can be made available on the net for fire rescue teams. This can be developed as an expert system to find fire indications earlier to warn fire managers in advance. Other areas of research include applying better segmentation techniques to extract the forest fire object and improved prediction methods to get reduced misprediction rates.

REFERENCES

[1] Rajasekar Umamaheshwaran, Wietske Bijker, and Alfred Stein, "Image Mining for Modeling of Forest Fires from Meteosat Images", IEEE Transactions on Geoscience and Remote Sensing, Vol. 45, No.1, pp. 246-253, January 2007.

[2] P.Stanchev, "Using image mining for image retrieval", IASTED Conference Computer Science and Technology, Cancum, Mexico, pp. 21-218, 2003.

[3] Stefan Voigt, Thomas Kemper, Torsten Reidlinger, Ralph Kiefl, Klaas Scholte and Harald Mehl, "Satellite Image Analysis for Disaster and Crisis-Management Support", IEEE Transactions on Geoscience and Remote Sensing, Vol. 45, No.6, pp. 1520-1528, June 2007.

[4] V. Karasova, "Spatial data mining as a tool for improving geographical models", Masters thesis, Dept. Surveying, Helsinki Univ. Tech, France, pp. 1-65, 2005.

[5] Richard J.Roiger and Michael W. Geatz, "Data Mining: A tutorial based primer", Pearson Education, First Indian reprint, 2005.

[6] Herbert Daschiel and Mihai Datcu, "Information mining in remote sensing image archives: System evaluation", IEEE Transaction on Geoscience and Remote Sensing, vol. 43, no.1, pp. 188-199, 2005.

[7] S. Anderson, M.Taylor, P. Sutton, M.Steinberg, "Assessment of urban land use cover changes in Cuidad Victoria, Tamaulipas, Mexico", www.isprs.org.

[8] Anil. K. Jain, "Fundamentals of Digital Image Processing", Pearson Education, Second Indian reprint, 2004.

[9] Margaret H. Dunham and S.Sridhar, "Data Mining: Introductory and advanced topics", Pearson Education, Second Edition, 2007.

[10] Ian H. Witten & Eibe Frank, "Data Mining: Practical machine learning tools and techniques", Elsevier, Second Edition, 2006.

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