An Autonomous Forest Fire Detection System Based On Spatial Data Mining and Fuzzy Logic

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Summary
The need for data mining applications in describing, explaining and forecasting spatial patterns has been on a steady increase owing to the huge rise in the number of civilian satellite repositories and the efficient utilization of remotely sensed earth observation data for the study of earth system. Fire is one of the major causes of surface change and happens in the mass of vegetation zones across the world. Forest fires are key ecological threats that lead to deterioration of economy and environment besides endangering human lives. The motivation behind this paper is to obtain beneficial information from spatial data and use the same in the determination of spots at the risk of forest fire by utilizing data mining and artificial intelligence techniques. In this paper we have proposed a novel approach to detect the forest fire automatically from the spatial data corresponding to forest regions with the aid of clustering and fuzzy logic. Initially, the digital satellite images are converted into CIELab Color Space and clustering is performed to identify the regions showing hotspots of fire. A fuzzy set is formed with the color space values of the segmented regions which are followed by the derivation of fuzzy rules on basis of fuzzy logic reasoning for the detection of forest fires. The proposed system has been evaluated with the help of publicly available spatial data corresponding to forest regions.

Key words:
Spatial data mining, Remote Sensing, Forest Fire Detection, Clustering, K- means clustering, CIELab Color Space, Fuzzy logic, Fuzzy set, Fuzzy rules.

1. Introduction

The combination of Databases, Artificial Intelligence and Statistics has led to the evolution of a contemporary field called Data Mining. This field has attracted voluminous research in the recent times. Knowledge discovery in data bases comprises of several precise steps. Data mining is the core step that leads to the identification of hidden yet beneficial knowledge from enormous amount of data. Knowledge discovery in data bases can be formally defined as: "The non trivial extraction of implicit, previously unknown and potentially useful information from data" [1]. A data mining system involves diverse user categories thus the user behavior needs to be a constituent of the system [2]. In general, data mining is classified into two categories namely descriptive and predictive data mining. The process of drawing the necessary features and properties of the data from the data base is called descriptive data mining. Some examples of descriptive mining techniques include Clustering, Association and Sequential mining. In case of predictive mining patterns from data are inferred so as to make predictions. Common predictive mining techniques include Classification, Regression and Deviation detection [3].

Data mining techniques have been successfully applied in many different fields, including marketing, manufacturing, process control, fraud detection and network management besides a variety of data sets like market basket data, web data, DNA data, text data, and spatial data [4]. The automated discovery of spatial knowledge is emphasized by the explosive growth of spatial data and widespread use of spatial databases [5], thereby leading to an increasing interest in mining interesting and useful but implicit spatial patterns [6, 7]. Mining knowledge from large amounts of spatial data can be referred as Spatial data mining, which is a demanding field since huge amounts of spatial data have been collected in various applications, ranging from environmental assessment and planning, remote sensing to geographical information systems (GIS), computer cartography [8]. The existent knowledge, the space relation or other meaningful modes of the space database are extracted by the spatial data mining technique. The mining of the synthetics data and spatial database are necessitated by spatial data mining [9]. The systematic structure of spatial data mining is depicted in Figure 1.

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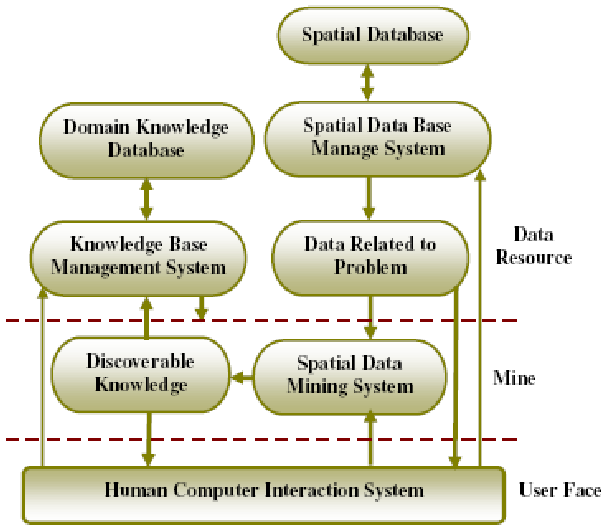

Fig. 1 Systematic Structure of Spatial Data Mining

Spatial data mining can be employed for the comprehension toward the spatial data, the detection of spatial relation and spaces relating to non-space, the structure of the spatial knowledge base, the administrative expense of spatial database and optimizing spatial query. Spatial Data Mining varies from the general business data mining due to the complexity of the space data resembling some characteristics [9]:

- Abundant data source, very huge quantity of data, many data types, complicated method of accessing;
- The applied realm is so extensive that the data related to space position can be excavated;
- There are several excavating methods and the arithmetic's and most of the arithmetic's are very complicated and difficult;
- The expressive method of the knowledge is diverse, and the comprehension and evaluation of knowledge depends on the person's cognitive degree to the objective world.

The detection, mapping and prediction of any phenomena that manifests a spatial pattern can apply the spatial data mining techniques. Forest fire, Drought, Flood and more particularly those with very large spatial extent, are a few spatial phenomena with predictable spatial patterns, which are observable through remote sensing Images/products. Our research mainly focuses on employing the spatial data mining techniques and fuzzy logic for the detection of forest fires from satellite images.

In this paper, we have proposed a system which will automatically detect fires from the spatial data corresponding to forest regions. The proposed system utilizes spatial data mining, image processing and artificial intelligence techniques for the detection of forest fires. The spatial data corresponding to the forest regions serve as input to the proposed system. The digital images from the spatial data are considered for the forest fires detection. The images with the presence of fires are used to form the fuzzy rule base in order to detect the fires. Initially the images are converted to CIELab color space. Conversion is followed by clustering of image in CIELab color space using the renowned K-means clustering algorithm. This will result in segments of the image prone to fires. The "a" value from the Lab color space of the fire regions are used to form the fuzzy set followed by the formation of fuzzy rules on basis of fuzzy logic reasoning. The fuzzy rules thus derived are used for the detection of forest fires. The proposed system has been evaluated with the help of publicly available spatial data corresponding to forest regions.

The rest of the paper discusses our approach and is organized as follows. Section 2 presents a brief review of some works on forest fire detection. Section 3 gives a concise description about forest fires. Section 4 introduces the concepts and techniques utilized in the proposed system. The autonomous detection of forest fires using clustering and fuzzy logic is presented in section 5. The conclusions are summed up in Section 6.

2. Related Works

Ollero et al. [10] have presented a scheme of multi-sensorial integrated systems for early detection of forest fires. They have used infrared images, visual images, data from sensors, maps and models in their system. Their study revealed the need to integrate sensors, terrain knowledge and expertise in order to minimize perception errors and improve the reliability of the detection process. Louis Giglio et al. [11] have presented an improved fire detection algorithm that offers increased sensitivity to smaller, cooler fires as well as a significantly lower false alarm rate. They have established the performance of the algorithm using a theoretical simulation and high-resolution Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) scenes.

Seng Chuan Tay et al. [12] have presented an approach to reduce the false alarms in the hotspots of forest fire regions. They have used geographical coordinates of hot spots in forest fire regions in the detection of likely fire points. `They used clustering and Hugh transformation to determine regular patterns in the derived hotspots and classify them as false alarms on the assumption that fires usually do not spread in regular patterns such as in a straight line. Their work demonstrated the application of spatial data mining to reduce false alarm from the set of hot spots derived from NOAA images.

Young Gi Byun et al. [13] have proposed a graph-based forest fire detection algorithm based on spatial outlier detection methods. They have used spatial statistics reflecting spatial variation in their algorithm. Their algorithm yielded higher user and producer accuracies than those of the MODIS fire product provided by the NASA MODIS Science Team. They have proven that the ordinary scatter plot algorithm was problematic in that it was not sensitive to small forest fires, while Moran's scatter plot was also weak for it entailed a more and less high commission error due to the absence of a numerical criterion for spatial variation.

Daniela Stojanova et al. [14] have proposed an approach to predict forest fires in Slovenia using different data mining techniques. They used predictive models based on data from a GIS (geographical information system), the weather prediction model - Aladin and MODIS satellite data. They examined three different datasets: one only for the Kras region, one for Primorska region and one for continental Slovenia. They have demonstrated that bagging and boosting of decision trees gives the best results in terms of accuracy for all three datasets.

Yasar Guneri Sahin [15] has presented a mobile biological sensor system for early detection of forest fires. The system used animals as mobile biological sensors. The system is based on existing animals tracking systems used for zoological studies. He has demonstrated that combining these fields may contribute to developments in both animal tracking and forest fire detection simultaneously. The system has detected potentially serious forest fires early, reducing their effect, thus helped to reduce the speed of global warming.

Florent Lafarge et al. [16] have presented a fully automatic method of forest fire detection from TIR satellite images based on the random field theory. They have demonstrated that their results only depend on the confidence coefficient. They have obtained convincing values for both detection rate and false alarm rate. They have obtained interesting information, related to the evolution of the fires through the estimation of fire propagation direction

Movaghati et al. [17] have studied the potential of agents to be applied in processing of remote sensing imagery. They have presented an agent based approach for forest fire detection. The agent utilized the tests used in MODIS version 4 contextual fire detection algorithm to determine agent behavioral responses. They have compared the performance of their algorithm with MODIS version 4 contextual fire detection algorithm and ground-based measurements. Their results showed good agreement between the algorithms and field data.

3. Forest Fires

Forest fires are a global concern causing a lot of damage and contributing to the deterioration of the Earth ecosystem, particularly to the global warming. The violation of functions in the natural systems and large number of fires caused by humans, although other factors like drought, wind, topography, plants etc., have important indirect influence on fire appearance and its spreading, damage the natural environment. Each year millions of forest hectares (ha) are destroyed all around the world because of the forest fires. As an all time high in the past 28 years, during the fires of 2007, an overall 575531 ha of land was destroyed in various European nations. From 1980 to 2006, about 1.33 million ha of forest land has been ruined by the fires. The fire seasons in the year 2007 were more than ever dramatic, affecting the territory, with some human deaths [18]. The threat to public safety and property cannot be exempted, even though the fires are considered a customary component of the Canadian forest ecosystems [19]. The evacuation of vulnerable communities has been forced occasionally besides heavy damages amounting to millions of dollars. Owing to the forest fires, which lead to degradation, Indian forests are also in jeopardy [20]. During the past few summers, owing to forest fires, the vegetation covers of the Garhwal Himalayas in the Himalayan forests are being deteriorated gradually.

At present, as an outcome of fire regime and landscape change there is a very limited understanding of the changes in diversity and structure of forests. It is important to study and address these issues, though, climate shifts can contribute to future changes in fire regimes. A successful firefighting necessitates fast detection, which is a key constituent. It is necessary to develop automatic solutions owing to the expensive traditional human surveillance and affect of subjective factors [21]. Remote sensing satellites have served as a source of geographical information in the recent times. Fire monitoring and management and fire damage assessment are carried out with key information obtained as a result of Satellite remote sensing [22]. The fire hot spots are located by the AVHRR sensors mounted on NOAA Polar Orbiting Satellites with channel 3 (3.8mm). Additionally, they also provide images that describe spatial distribution and temporal evolution of the fire hotspots [23].

4. Prerequisites

This section briefly describes the concepts and techniques employed in the proposed system

4.1. Color Space

We can specify, create and visualize color by employing the color space method. A color is defined by humans in terms of its attributes of brightness, hue and colorfulness. The display of color is precisely specified by the color space method which employs a three-dimensional coordinate system [24]. Transfer of data between devices that employ different color space models often necessitates color space conversion, in which the representation of a color is translated from one basis to another. Usually, the context of converting an image that is represented in one color space to another color space employs a color space conversion. The objective is to make the translated image look as similar as possible to the original.

The $L*a*b$ color space is the most beneficial and widely utilized color model. In 1976, the *CIE* developed a new color space $L*a*b$ by refining the XYZ color model [25]. $L*a*b$ describes every color as three components and is device independent, similar to the XYZ. In this case, the luminance value L varies uniformly from 0 for black to 100 for white. The values of a and b are expressed such that red/green are indicated by $+a/-a$ and blue/yellow are indicated by $+b/-b$.

RGB To $CIEXYZ$ conversion:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412435 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$CIEXYZ$ To $CIELab$ conversion:

$$L* = \begin{cases} 116(Y/Y_n)^{1/3} - 16, if \quad Y/Y_n > 0.008856 \\ 903.3(Y/Y_n), \quad if \quad Y/Y_n \le 0.008856 \end{cases}$$

$$a* = 500 * (f(X/X_n) - f(Y - Y_n))$$

$$b* = 200 * (f(Y/Y_n) - f(Z - Z_n))$$

$$\text{Where } f(t) = \begin{cases} t^{1/3}, \quad if \quad t > 0.008856 \\ 7.787 * t + 16/116, \quad if \quad t \le 0.008856 \end{cases}$$

Here X_n, Y_n and Z_n are the *CIEXYZ* tristimulus values of the reference white point (the subscript n suggests "normalized").

4.2. Clustering

Clustering is the classification of objects into different groups, or more specifically, it refers to the partitioning of a data set into subsets (clusters), in order that the data in each subset (ideally) share some common trait - often proximity according to some defined distance measure [26]. In image clustering, the pixels are classified into groups (clusters) in an unsupervised manner. The clustering problem has been addressed in many contexts and has shown to be useful in many applications. On the other hand, clustering is a combinatorial difficult problem. Several methods are available in the literature for image clustering: K-means [26], fuzzy c-means [29], region growing [27], split and merge [28], information bottleneck [34] and tensor representation [35]. We have employed the renowned K-means clustering algorithm in our system

4.2.1. K-Means Clustering

The well known clustering problems are solved with the aid of a very simple unsupervised learning algorithm called the K-means [26]. The K-means algorithm segments an image into K clusters in an iterative fashion. The algorithm can be described as follows:

- K cluster centers are picked either at random or on basis of a heuristic
- Each pixel in the image is assigned to a cluster in such a way that the variance between the pixel and the centre of the cluster is minimal.
- Re-compute the cluster centers by averaging all of the pixels in the cluster
- Repeat steps 2 and 3 until convergence is attained. (e.g. no pixels change clusters)
- Here, the variance is either the squared or the absolute difference between the cluster center and the pixel. The pixel color, intensity, texture and location or a weighted combination of all these factors determine the difference. The value of K can either be selected manually, randomly, or on basis of a certain heuristic.

Though the algorithm is guaranteed to converge, an optimal solution might not be obtained. The initial set of clusters and the value of K play a vital role in determining the quality of the solution [30]. The beneficial features of this algorithm such as simplicity and speed facilitated the algorithm to be executed on large datasets. The algorithm succeeds in minimizing the intra-cluster variance whereas fails to ensure that the result has a global minimum of variance [31]. K means has been implemented in various problem domains with regard to its simplicity.

4.3. Fuzzy Logic

The theory of fuzzy logic was introduced by Zader Lofti in the late 1960s [32]. Prior to this Lukasiewicz put forth the multivalued logic and thus the fuzzy logic is regarded as a rediscovery of that approach. Fuzzy logic is an extension of Boolean logic facilitating the concept of partial truth i.e. truth values between “completely true” and “completely false”. As the name implies the modes of reasoning are not accurate but approximate. Fuzzy logic has gained importance from the fact that numerous human modes of reasoning and common sense reasoning are approximate in nature. Fuzzy set approach was introduced for representing the real world scenarios that could not be represented with just two values. The fundamental constituents of fuzzy logic decision making system include fuzzy sets, fuzzy membership functions and fuzzy rules. A membership function is of vital significance in a fuzzy set.

5. Autonomous Forest Fire Detection System

In this section, the proposed autonomous forest fire detection system is presented. The proposed system utilizes spatial data mining, image processing and artificial intelligence techniques for the detection of forest fires. The spatial data corresponding to the forest regions serve as input to the proposed system. The fire detection is performed on the images of the spatial data. A fuzzy rule base is formed for detection of fires from the spatial data with the presence of fires. The steps involved in the fuzzy rules formation are as follows:

i. Convert the digital images from RGB to $CIEL*a*b$ color space. The $a*$ value of the $CIEL*a*b$ color space accurately represents the pixels corresponding to fire.
ii. Perform clustering on each image using the prominent K-means clustering algorithm. The clustering is performed to detect fire regions. Fuzzy rules are formed with the aid of clustered regions affected by fire in the image.
iii. Form a fuzzy set with the $a*$ value of the regions where fire prevails and generate fuzzy membership functions.
iv. Derive fuzzy rules from fuzzy set and membership functions using fuzzy logic reasoning

The formation of fuzzy set, membership functions and fuzzy rules for the detection of forest fires are explained in the following sub section.

5.1. Fuzzy Set, Membership Function and Fuzzy Rule Formation Using Fuzzy Logic Reasoning

Fuzzy sets, fuzzy membership functions, and fuzzy rules form the majority of the fundamental elements of a fuzzy logic system. A fuzzy set is has no defined boundaries. There is a regular and even transition from “belonging to a set” to “not belonging to a set” and this is defined by membership functions. Fuzzy sets are employed to model general linguistic expressions such as ”the object is dark” or ”the object is round” and these functions provide flexibility required by the fuzzy sets in such modeling [33].

A fuzzy set is defined as follows: If S is a collection of objects, then a fuzzy set FS in S is defined as a set of ordered pairs:

$$FS = \{(s, mf(s)) \mid s \in S\}$$

Where, $mf(s)$ is the membership function of s in S. The value of the membership function ranges from 0 to 1 and can be considered a degree of truth. Fuzzy rules are derived from these fuzzy sets. A fuzzy rule base can contain much number of fuzzy rules. The structure of a fuzzy rule is the following:

IF Premise THEN Conclusion

Where the premise consists of antecedents linked by fuzzy operator AND.

In our system, the $CIEL*a*b*$ color space values serve as the Universe of discourse for the fuzzy logic. The fuzzy set $DR(x,x,x)$ is formed of ordered pairs of $CIEL*a*b*$ color elements and their corresponding degree of membership. The membership function is defined on the basis of the $a*$ value of the $CIEL*a*b*$ color space. Then the fuzzy sets are formed from the color space values based on the membership functions. Then fuzzy rules are derived from the fuzzy set using fuzzy logic reasoning for the detection of forest fire.

The fuzzy set wherein $L*a*b*$ color space is employed for determining the degree of membership is defined as follows:

$$
\begin{aligned}
Fuzzy\ CIEL*a*b*(x) = \{ & 0, \text{ if } ([M_N < a*valueof(x)] \text{ and } [M_X > a*valueof(x)]); \\
& 1, \text{ if } ([a*valueof(x) >= (M\ a_{Min})] \text{ and } [a*valueof(x) <= (M\ a_{Max})]); \\
& \text{if } ([a*valueof(x) >= (M_N)] \text{ and } [a*valueof(x) <= (M\ a_{Min})]); \\
& (abs(M\ a_{Min} - a*valueof(x)))/100 \text{ ; degree of membership }. \\
& \text{if } ([a*valueof(x) <= (200)] \text{ and } [a*valueof(x) >= (M\ a_{Max})]); \\
& (Ma_{Max} - a*valueof(x))/100 \text{ ; degree of membership } \}
\end{aligned}
$$

Where

(x) → Set of selected pixel value

M_N → Minimum value of $a*$ (175)

M_X → Maximum value of $a*$ (200)

$M\ a_{Min}$ →Minimum Median value of $a*$

and defined as

$$M\ a_{Min} = [(a_{Min} + a_{Max})/2] - \hbar$$

$M\ a_{Max}$ →Maximum Median value of $a*$

and defined as

$$M\ a_{Max} = [(a_{Min} + a_{Max})/2] + \hbar$$

$\hbar$ → Small value varies from 0 to 5

6. Conclusion

Environmental deterioration and threat to human lives are caused by forest fires. The autonomous detection of forest fires from spatial data has gained popularity in recent years because of the large volume of spatial data available. Efforts were put forth in the recent decades to develop automatic detection tools that could aid the Fire Management Systems (FMS). Contemporary trends include infrared/ smoke scanners and local sensors. A novel system for identifying forest fires autonomously from digital images of spatial data has been projected in this paper. The proposed system has made use of CIEL*a*b color space. K-means clustering has been employed for the clustering of pixels and the detection process has been carried out with the aid of fuzzy logic. The fuzzy sets have been formed from the $a*$ values of the $CIEL*a*b*$ color space correspond to fire regions and fuzzy rules have been derived from the fuzzy sets. The fuzzy rules thus formed have efficiently detected the fires. The evaluation has been done with the aid of publicly available spatial data.

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