Chapter 6 Hot Spot Identification Systems for Wildfire Control

Capítulo 6 Sistemas de Identificación de Puntos de Calor para Control de Incendios Forestales

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Abstract

One of the most common problems that today's society with climate change is the increase in forest fires in various parts of the world. The present investigation refers to a literary review of the investigations carried out on the development of proposals that allow the identification of fire situations in natural ecosystems. The presence of fire is identified using computational systems that combine computer vision, artificial intelligence, and sophisticated monitoring variables that may indicate the presence of fire in a natural area. According to the research carried out, interesting models have been developed for the recognition of fire and its early detection, through advanced statistical processes, regression systems, and constant monitoring of the variables that intervene in the generation of fire.

Computer vision, Artificial intelligence, Hot spots, Forest fires

Resumen

Uno de los problemas más comunes que enfrenta la sociedad actual con el cambio climático es el aumento de los incendios forestales en varias partes del mundo. El presente trabajo hace referencia a una revisión literaria de las investigaciones realizadas sobre el desarrollo de propuestas que permitan identificar situaciones de incendio en ecosistemas naturales. La presencia de fuego se identifica mediante sistemas computacionales que combinan visión por computadora, inteligencia artificial y variables de monitoreo sofisticadas que pueden indicar la presencia de fuego en un área natural. De acuerdo con las investigaciones realizadas, se han desarrollado interesantes modelos para el reconocimiento del fuego y su detección temprana, mediante procesos estadísticos avanzados, sistemas de regresión y monitoreo constante de las variables que intervienen en la generación del fuego.

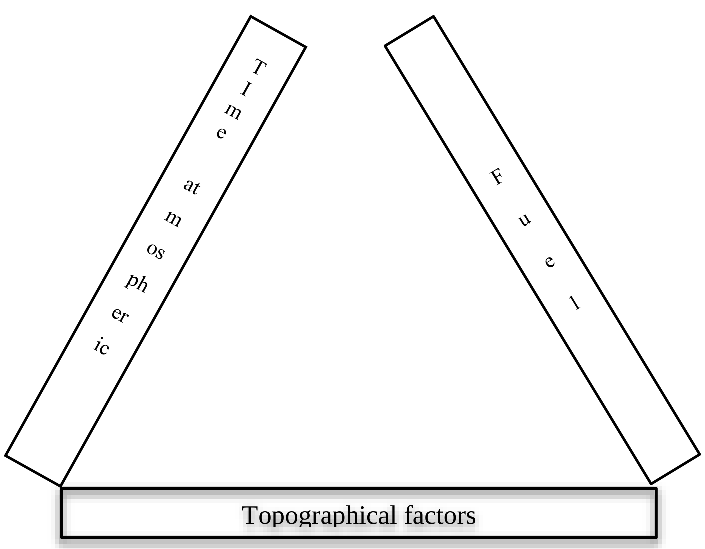
Visión por computadora, Inteligencia artificial, Puntos de calor, Incendios forestales

Introduction

Climate change, together with ground pollution and the uncontrolled release of garbage that contaminates water and subsoil, among other types of human carelessness are the main causes of forest fires in various parts of the world, being 96% of the causes of these events by activities carried out by man (Semarnat, 2018). Uncontrolled forest fires generate large losses of wild regions, destruction of human settlements and increased pollution at the atmospheric level (Cruz-Lopez, Manzano-Delado & Aguirre-Gómez, 2019). While it is true that the cycle of fire in ecosystems has to do with the renewal of these as a normal cycle of its existence (He et al., 2012), (Bowman et al., 2016) , (Keeley et al., 2011), oversights and elements that do not belong to the fire cycle condition its stability (Villers-Ruíz, 2006).

Fuel, weather, and topographic factors are some of the main variables involved in the generation of fires.

Figure 1 Forest Fire Triangle



Source: Own Elaboration

Figure 1 represents the triangle of fire (Sutton, 2015), in which fuels are contemplated, which are the objects flammable, among them are trees and grasslands; the weather represents the conditions that are currently in the environment, taking into account that the weather conditions that favor high concentrations of oxygen and winds allow the fire to expand at a higher speed; finally, topographic factors are present, which determine whether or not there are natural barriers for the fire to spread or stop.

Globally, forest fires cause a release of 6.375 billion tons of carbon dioxide (CO2) (Green Peace, 2019). Approximately more than 30 million km^2 are affected by forest fires worldwide (Randerson et al., 2012). The smoke released from wildfires contains hazardous particles such as PM10 and PM2.5 (particles measured in microns) and are highly hazardous (Vicente et al., 2013), because when inhaled by humans can enter the bloodstream, causing lung and cardiovascular problems (Wettstein et al, 2018), (De Florio-Barker et al., 2019), (Adetona et al., 2016).

In the period between 2000 and 2010, only in Mexico more than 1.95 million hectares of forest were lost, while in the period from 2010 to 2020 the loss of 4.5 million hectares was reported losses due to more than 7,500 fires, which grew without control (CONAMER, 2013). The entities of Mexico that concentrate most of the forest fires are the State of Mexico, Mexico City, Chihuahua, and Michoacan which present more than 52% of the fires in the country (CONAFOR, 2021).

Due to the problems represented by forest fires, numerous works have been developed dedicated to the prevention, identification, and control of these. These works have focused on the use of technologies such as Wireless Sensor Networks, also known as *Wireless Sensor Network* (WSN) which are composed of tens or thousands of electronic sensors powered by batteries, called sensor nodes, which are distributed throughout an area of particular interest to monitor variables in the environment that indicate some important event (Chio Cho et al. , 2011).

Another technique used for the detection of forest fires is the identification of objects in images or video using *convolutional neural networks* (CNN), which are a variant of an artificial neural network where neurons correspond to receptive fields like neurons in the visual cortex. primary brain of a living being (Cruz et al., 2021), being one of the most common applications of deep learning (DL) (Bacioiu et al., 2019). Networks are trained with pure data or with characteristics obtained manually.

Another technology that allows locating events in geographical spaces are geographic information system (GIS), which are an organized set of hardware, software, and geographic data, oriented to capture, store, manipulate, analyze, and display geographically referenced information to solve complex problems that are related to the planning and management of a process (Moreira, 1996).

The following section presents a compilation of proposals that have been developed in Mexico and other countries to detect hot spots that represent forest fires, as well as studies on the effectiveness of currently available tools.

Fire identification: Proposals in the state of the art

In the analysis of hot spots there is a diverse range of research that addresses different methodologies and technologies to determine if a forest fire is developing, as well as the efficiency of these. One of the investigations that address the efficiency of forest fire detection systems using satellite technology is González-Gutiérrez et al. (2019), which performs an analysis on the reliability in the identification of hot spots in the state of Michoacán, Mexico.

This research shows the evaluation of the effectiveness of the Early Warning *System* for Forest *Fires*, this system has been in operation for approximately 34 years, however, the effectiveness of the system had not been proven, as a result of the investigation the authors point out that the CONAFOR (National Forestry Commission) system only detects fires that exceed 50 ha (hectares), therefore, authors suggest a change in the way fires are detected, so that technology included in focused points for a more efficient detection of forest fires.

In Pompa-García & González (2011) evaluated the fires that occur in the state of Durango and Mexico to detect which fires had greater proliferation, discovered that in the ecosystems where trees such as pine, oak and grasslands proliferate, different behaviors were detected. The authors detected that a fire where there was pine and oak this was presented in a group, while in areas where there is grassland, the fire occurs randomly.

Convolutional neural networks have high performance at object detection, but computationally come at a high cost. When implementing this type of network models in mobile devices or in low-cost *Internet of Things* (IoT) devices for object detection, the detection process is slow, as noted in the work of Lawrence & Zhang (2019), for this reason, the authors propose a model called IoTNet for resource-limited devices in object recognition using CNN. In Jardon, Varshney & Ansari (2020) propose an efficient fire detection method integrated and compatible with mobile devices. The results obtained in several standard fire datasets with the proposed method were superior to all existing methods in terms of most evaluation metrics such as accuracy, precision, recovery, and measurement, as noted in the paper. The proposed method is based on the CNN architecture called MobileNetV2.

In the investigation of Camacho, Díaz-Ramírez & Figuero (2015) exposes a network of sensors, which collected information on the environmental temperature and relative humidity under normal conditions, the authors realized that, when the temperature increased, the value of humidity decreased. The authors present the techniques of interpolation and the use of the Dempster-Shaner theory, to determine if there is a fire, although indicate that its effectiveness is low, given the variations provided by the model. Finally, the authors chose to use regression functions, taking time as an independent variable, and variables such as temperature and humidity were taken as dependent. The model proposed by the authors was evaluated in a middleware based on Java, and the sensor network platform used was IRIS. The result that authors obtained was 100% detection when the sensor nodes are not directly exposed to the sun.

Another application of a sensor network is observed in Hernández-Hostaller (2017), where propose the integration of temperature, carbon monoxide (CO), smoke, and infrared sensors. The acquired data is compared with a knowledge base to determine if there is a fire according to the data obtained by the sensor network, detecting the variations expected when simulating a fire.

The sensor networks require a series of considerations that allow them to effectively detect the variables are monitoring, in the work of Kim et al. (2020) perform an optimization in the WSN for the reduction of energy consumption and signal detection, which is applied to fire detection, through Continuous Object Tracking Based on Origin (OCOT), emphasizing distributed data, allowing a 49% reduction in network energy consumption without losing effectiveness in the detection of elements.

Computer vision systems have benefited from deep neural network models such as YOLO (*You Only Look Once*) (Redmon et al., 2016), this pre-trained model was implemented for numerous applications that require identification of objects that are contained in digital images or video. One of the applications that exists for identifying forest fires through the YOLO network is found in the work of Zhao (2022), in which developed a dataset (collection of elements) of 370 images containing fire and smoke situations with dimensions of 1850 x 1850 pixels. The authors made a modification on the convolutional network and named it Fire-YOLO, to later compare it against YOLO-V3 and Faster R-CNN (Girshick, 2015). In the project achieved a detection percentage of 76%, considering that the fire sections do not occupy more than 10% of the total image, compared to other models that require large portions of the image to perform the detection. The method implemented for building Fire-YOLO was Efficient Net.

There are other proposals whose solution is based on the integration of drones (also called unmanned aerial vehicles or UAVs) as can be seen in the work of Kinaneva (2020) in which use a series of drones which have digital image processing capabilities to detect forest fires. Meanwhile in the work of Rajeshwari (2019) present a proposal for capturing thermal images for fire detection, successfully detecting the areas in which a forest fire is located.

In some other proposals, in Parajuli (2020) and Zhao et al. (2021), carried out work to identify forest fire risk areas in Nepal and Nanjing, respectively, where present a characterization model of areas where forest fires can occur using information from GIS, because these systems allow to include information such as altitude, coordinates, reliefs, demarcation of zones by temperatures, presence of ecosystems, among others, allowing to identify the areas of greatest risk, to carry out preventive monitoring and prevent the spread of forest fires. As can be seen, there are different proposals that, based on software implementations, obtain information from different types of hardware to determine if there is the presence of a forest fire for prompt attention.

Wildfire identification technologies

One of the primary challenges that exist to reduce forest fires is the process of raising people's awareness about actions not to throw garbage, as well as avoiding intentional burning activities to develop activities such as agriculture and livestock. On the other hand, the other challenge that exists is the early detection of a fire, as well as the prediction of its evolution to avoid a rapid spread. Some points that was analyzed from the information collected previously in the works of González-Gutiérrez et al. (2019), Pompa-García & González (2011), Lawrence & Zhang (2019), Hernandez-Hostaller, (2017) Zhao (2022) and Parajuli et al. (2020) is that forest fire detection systems should consider the following elements.

– Monitoring of variables such as temperature, humidity, and presence of combustion gases such as CO, CO_2, as well as PM10 and PM2.5 particles.
– Identification of geographic areas that contain the highest probability of a fire, such as places with a lot of fuel and lack of moisture.
– Control of false positives and false negatives for parameters not contemplated.
– Presentation of possible decisions to prevent, contain or extinguish fires.

Is possible identified that there are four current trends for fire identification, such as detection by satellite imagery, detection by sensor networks, detection by capture of digital images and video using machine learning and GIS based models. Table 1 presents the most important advantages and disadvantages for forest fire detection.

Table 1 Fire detection technology

Detection technology	Advantages	Disadvantages
Satellite reconnaissance	- These systems can collect a large amount of information related to reliefs, weather conditions, as well as capture vast extensions of territory in digital images.	-These systems present difficulties to detect fires with an extension of less than 50 ha. - To access the information captured by these systems it is necessary to have connections via the internet.
Sensor networks	- These networks can act in specific places because can cover areas of several hectares. - WSN can monitor many variables such as temperature, relative humidity, presence of harmful gases, among other elements.	- WSN depend on the configuration of the central system to establish the appropriate parameters of the detected variables, because cause false positives or late alerts.
Deep Learning Recognition	-DL is highly efficient for detecting specific elements that have been captured in digital images and video. -DL can process information from different color models, as well as events captured by infrared technology. - DL can be implemented on a wide range of hardware.	-DL depend highly on rigorous training based on information contained in databases with many elements that present different contexts. - CNN is generally characterized by a high consumption of computational resources for its training, as well as for its operation. - CNN are not suitable for deployment in devices with low computational resources or that depend on batteries, without a control of energy consumption.
GIS	- GIS contain a large amount of information about the geographical points where the fires occur, because have information on the reliefs, terrestrial coordinates, among other elements, which allows classifying the risk areas.	- GIS depend on relatively constant updating and support from other systems for operation.

Source: Own Elaboration

The different technologies that are mentioned in a general way in Table 1, have allowed to attack the problem of fires from different points of view, but it is possible to note that none of them can face the problem with 100% effectiveness in real conditions, because the contexts that can be presented are highly varied, with many restrictions, which condition the mathematical models that are implemented, because variables such as luminosity, weather conditions, bodies that are obstructing the visibility of fires, among others, are present. As mentioned above, satellite technology presents one of the first solutions for the early detection of forest fires, but it is conditioned to areas that exceed 50 ha of extension, on the other hand, accessing this system requires stable internet connections and other types of permits (with government or private entities), for this reason, the recognition by deep learning based on CNN, whose algorithms care implemented in different types of hardware makes them versatile in situations where the budget is reduced, allow mobility and as well as effective communication with personnel dedicated to fighting forest fires. This technology is implemented in IoT devices and unmanned autonomous vehicles (UAVs), whose collected information is analyzed on site or on servers, although UAVs have the limitation of wide energy consumption and a late response in devices with low computational power. Figure 2 shows an example of fire detection in a CNN image, where the result is framed in violet.

Figure 2 Detection of the presence of fire in a wooded area. Image obtained from Kaggle dataset, own detection using YOLOv5

Source: Gamaleldin, et al. (2018)

In the case of using IoT devices, such as Raspberry (Figure 3), require a continuous and stable power supply, in addition to the fact that when working continuously requires an effective power system to avoid greater energy consumption, which presents a problem to be solved in continuous operation, because battery banks usually limit current consumption when demand is at the limit of its capacity.

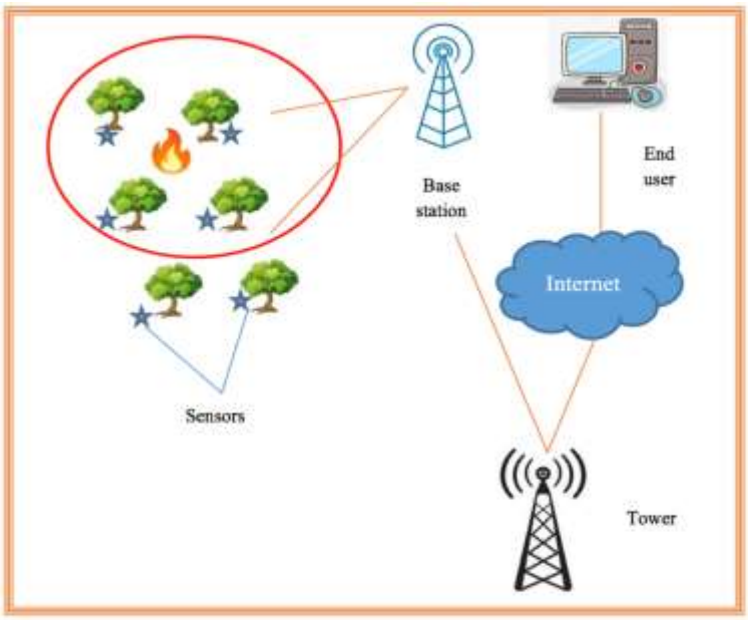
Figure 3 Raspberry Pi 3 B, one of the most widely used IoT

Source: Raspberry, (2018)

Sensor networks are an effective solution when monitoring the data that is captured from environments, especially when constantly monitoring temperature, humidity, and different types of gases, as well as the presence of PM10 and PM2.5 particles but depend extensively on the identification of thresholds that indicate the presence of a fire, as well as ensuring that the connection to the main base is stable.

Another challenge that sensor networks have is that nodes exposed to direct sunlight present problems due to the escalation of temperature, as well as the decrease in humidity, indicating that there is a fire, which is not present (false positive), and therefore, must consider different types of sensors. Figure 4 presents the basic scheme of a network of sensors for fire detection, where is possible see the basic components, such as sensors, the base station that is responsible for receiving the data, and the infrastructure available to make a link to the internet and send the data to the end user for decision making.

Figure 4 Schematic of a sensor network



Source: Zareei, et al., (2018)

One of the interesting developments that have been presented for computers is that of GIS systems, in which different types of geographic information are found, to identify the points of greatest incidence, these systems have the coordinates, and through GPS technology (*Global Positioning System*) it is possible to make tours with drones in an automated way for the early detection of forest fires.

Conclusions

Forest fire detection systems have a remarkable evolution in the last 15 years, because the development in technology with electronic components has allowed the computing capabilities of the hardware to rise and allow better processing capabilities and data transfer speed, this is essential when equipment of contained size and fast processing is required, this benefits the implementation of machine learning algorithms that allow recognizing early fire situations, especially in areas where available satellite technology has detection limitations.

Recognition systems based on machine learning, which use models based on CNN, have proven to be effective in detecting fire events, in addition to its implementation is possible carried out on different types of platforms, although have limitations such as high computational consumption in the training stage. Reconnaissance models based on deep learning can be implemented in servers, personal computers, portable devices, autonomous flight devices, among others, which gives a high versatility for the recognition of forest fire situations.

Sensor networks are highly effective when it is necessary to cover areas in which satellite technology is not able to quickly identify a fire, when it is in an area less than 50 ha, but knowledge bases are needed with very precise data that allow the implemented mathematical models to have an answer as accurate as possible, and an interpretation of the data obtained by the sensors with a series of perfectly defined ranges to avoid false positives or activation of alarms late. It is also important to note that the location of the sensors must be positioned in places where factors such as sunlight are not in direct contact with them, because alter its behavior.

Current GIS having a large amount of geographic information, allow the creation of models to identify fire risk areas in times of drought and high temperatures, are highly useful for the prevention of this type of event.

While it is true that the recognition models offered by artificial intelligence, as well as the recognition models implemented in sensor networks, can provide certainty that can reach more than 90% of the presence of a forest fire, both proposals need further development, which allows them to unify the most important characteristics of each one to offer robust systems that can attend with a greater effectiveness of its primary objectives.

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