ID – 10138 Session 2022
Overhead Lines – B2
Preferential Subject: PS3 - Environmental and Safety Aspects from OHL

Wildfire detection system using artificial intelligence with the collaboration of the web society

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SUMMARY

Intensifying in the years of 2000, the Overhead Transmission and Distribution Lines – OHL are seen by a part of society as agents that are harmful to the environment, despite the quality of life that they bring through the supply of electricity. Society has been urging against of O&M procedures and new OHL infrastructure nearby their land. The challenge is how to bring this society closer to the OHL. This goal was the original target for innovating through a pilot R&D project regulated by ANEEL – Brazilian Agency of Electric Energy, in which the voluntary web society job can be offered through internet access. The website wildfire images not only allow users on the web to confirm alarms automatically generated by the system with artificial intelligence, but also to monitor the camera images in real time and indicate the presence or not of smoke or fire near OHL. Currently the prototype pilot web system has more than 250 volunteer web users. They help monitoring the images produced by cameras installed in three different regions for test cases. The quick decision and action by the competent authority is made possible through the website system due to the collaboration of web society in the task of labelling the images that will be classified by the artificial intelligence system. The deep learning artificial neural network responsible for the detection of wildfires via computer currently has an accuracy rate of around 76%. It is expected to reach 80% accuracy with the increase of the image bank and improvement of training techniques, where such a precision measure considers both false alarms (i.e. false positives) and alarms that should have been generated but were not (i.e. false negatives). The neural network has been adjusted so that it is not difficult to recognize a real wildfire, though this tunning tends to generate more false alarms. Avoiding such false alarms has been a challenge and the most frequent confusions are (i) sun rays, reflections in water, raindrops and fog with smoke and (ii) sunsets and lights with fire. Interestingly, some outbreaks of wildfire detected by the neural network would hardly be detected by a human being, which is an indication that the neural network is overcoming the monitoring capacity of human beings. Despite the various advances achieved, there are still several challenges to overcome, such as sharing infrastructure of web digital cameras in complex OHL, improving the accuracy rate of detection, and improving web user interaction, which remains to be worked out.

KEYWORDS

Overhead Transmission Lines, Wildfire, Neural Network, Artificial Intelligence and Video Camera

1 INTRODUCTION

The wildfires cause interruptions in the supply of electricity and are also responsible for destruction of Brazilian flora and fauna. The Figure 1 shows the fires focus historical series in Brazil and statistical series of Minas Gerais state between 1998 and november of 2021 from Aqua Earth-observing satellite mission [1]. According to the National Institute for Space Research (INPE), Minas Gerais State has already registered 12,023 yearly fire spots up to Nov/2021 [2].

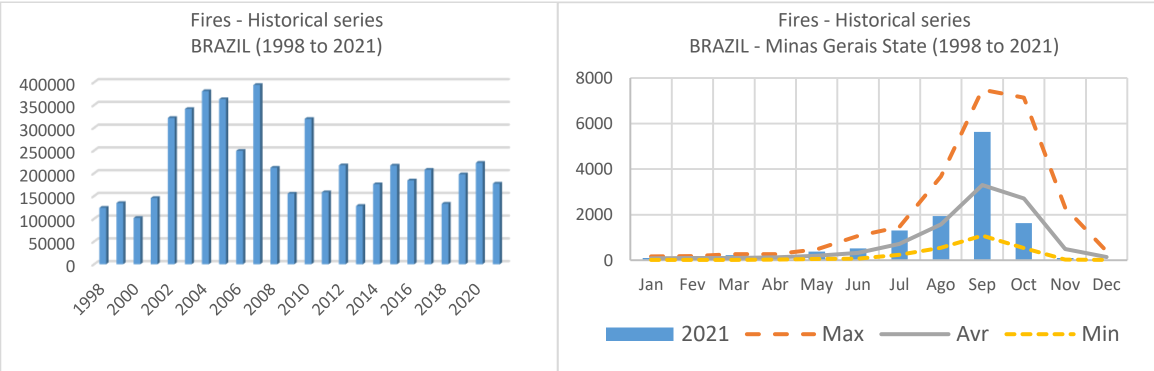
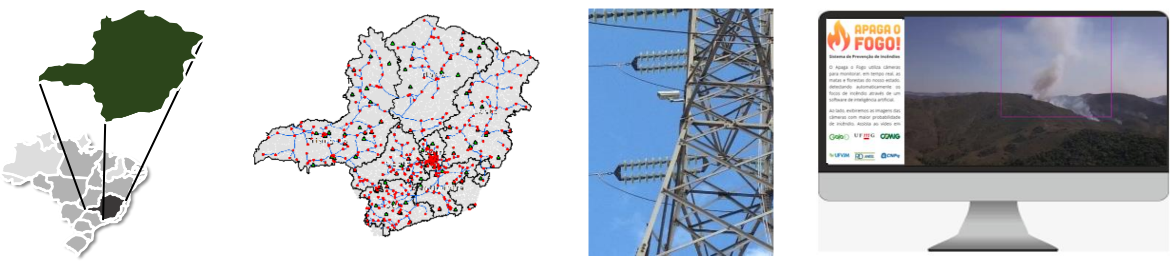


Figure 1 Fire Risk in Brazil and Minas Gerais State between 1998 and November 2021.

According to a Cemig Utility, the main causes of wildfires in Minas Gerais State are: the preparatory burning of pastures and land for planting, especially in periods of high temperatures and low air humidity; burning garbage; cigarette stubs thrown on roadsides, hitting dry vegetation; in addition to lightning. Generally, in Brazil, fire is used as an efficient and cheap soil preparation tool for these purposes. When reaching transmission lines and distribution networks, wildfires can cause the rupture or collapse of these structures and conductor, with the burning of wooden poles and crossarms and, consequently, the interruption of the electricity supply. In these cases, to reconnect the affected circuits, it is necessary to recompose the materials, an activity that requires a longer time to be performed. There is also the risk of short-circuits in overhead transmission and distribution lines, caused by heating the conductor above the design values.

With a distribution network over 500,000 km long and over 20,000 km of overhead transmission lines (138 and 230 and 345 and 500 kV) CEMIG Utility is responsible for supplying electricity to more than 8,5 million clients in Minas Gerais State of Brazil. In this way, one can think of using the Cemig's assets to help with environmental monitoring as showed in the Figure 2. And, in this way, placing this important asset of overhead lines and networks with one more noble role in the search for reducing wildfires. This work was developed through the Brazilian Energy Agency of R&D named “Environmental monitoring using real images of areas covered by overhead transmission lines using pattern recognition”.



(a) (b) (c) (d)

Figure 2 a) Cemig's assets with monitoring predicting wildfire, b) Cemig electric network in Minas Gerais state of area 586,528 km² (similar France country 643,801km²), c) video camera on Lattice Tower of 138 kV and d) webpage interphace of algoritms system for the detection of fire and smoke interaction with society.

Figure 1 shows an increase in the records of wildfires focus count in Brazil last two decades. Then, the application of this technology can represent an important ally in the combat and prevention of future wildfires in previously monitored areas. The system makes available, in real time, the images and digital processing autonomously, through computational intelligence algorithms for internet voluntary users. Users (internauts), in turn, will be able to help in the early and accurate identification of smoke sources, as well as in determining the evolution of fire wildfire sources. In this way, it will be possible, for example, to trigger alarms for the responsible authorities, via the web.

This paper presents a theoretical framework and a computational system for the detection of fire and smoke using computer vision and voluntary interaction with society. The goal was to make available, online and in real time, images of smoke and fire spots in environmental preservation areas near the assets of power transmission & distribution lines, in order to quickly fight the flames. Several computer vision techniques have been developed to generate alarms automatically using neural network with deep learning in artificial intelligence strategies. The system makes it possible to record both manual and automatic alarms, generating a knowledge base for improving the computing methods developed. The alarms indicated by different web users can be used as a database to refine the computational techniques that it will be presented in this paper. Certainly, one of the difficulties to apply techniques in this type of problem is the generation of segmented images with the objects of interest. The option made was the development of initial algorithms with a restricted validation base and the subsequent improvement of the methods with segmented videos (indicated as fire and smoke) by the volunteers, users of the Web system, validated by project development team. In addition to being a cost-effective way to generate a segmented database, it brings the immediate involvement of society into the project.

2 PROJECT TECHNOLOGY DEVELOPMENT

The Overhead Transmission and Distribution Lines – OHL expansion, which has intensified since the beginning of the century, has contributed to the global economy with important investments in clean energy supply. However, OHLs are seen by some segments of the society as harmful to the environment surrounding their right of way (ROW), despite the quality of life that they bring through the supply of electricity. There has been increasing pressure against O&M procedures and the construction of new OHL infrastructure, as shown in Figure 3. This issue was discussed in Cigre's Paris Technical Session in 2014 [3]. Then, decrease the society constraint OHT was the innovation and motivation adopted.

Figure 3 Society has been pressuring against O&M procedures and the construction of new OHL infrastructure on their land.

2.1 First stage of development

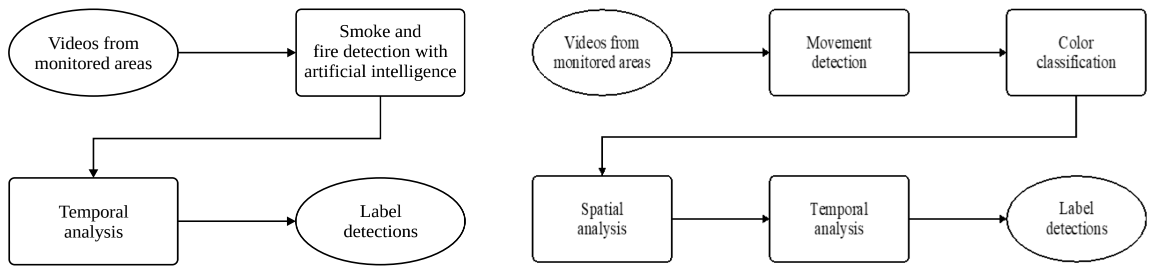
In the first stage, images and videos containing fire and/or smoke were collected from the Internet for the development and validation of the system. Regions of interest were then defined for each image through manual segmentation. Images that could potentially confuse the detection system, such as fog or sunbeams passing through leaves, were deliberately included in our database. The work focused on daytime images captured under different lighting conditions and focal lengths. In general, fire is easier to detect in night images since it usually is the only light source in the scene.

Separate algorithms were developed for fire and smoke detection. In either case, the method consists of 6 steps, as shown in Figure 4(a): i) video capture, ii) segmentation through background subtraction, iii) classification of fire and smoke color, iv) spatial analysis of pixels, v) temporal analysis of pixels, and vi) generation of alarms. Initially, both algorithms try to detect motion, since movement is usually associated with the elements of interest (fire and smoke). Detection works on three levels. In the first level, the color of the elements that make up the scene is considered. In the second level, the characteristics of the movement are analyzed. This helps, for example, to distinguish between smoke and a cloud, which may be the same color but move differently (smoke usually moves faster than clouds). Finally, the third level performs an analysis of persistence. The idea here is that if a certain color is present in a region for a long time, it is not characteristic of fire[4]-[11].

2.2 Second stage of development

The white box model developed in the first stage of the R&D project reached its state of the art generating many false alarms. An alternative black box model using artificial intelligence was adopted since the beginning of the second stage of R&D project and it has delivered a great increase in detection accuracy. This new approach is based on a Convolutional Neural Network (CNN) trained on an expanded version of the database containing thousands of labeled images.

In this new system, a single algorithm handles both smoke and fire detection. As shown in Figure 4(b), the method is organized into 4 steps: i) video capture, ii) detection using artificial intelligence, iii) temporal analysis, and iv) alarm generation. The artificial intelligence (AI) is performed by an object detection algorithm called YOLO (You Only Look Once), which is implemented through a Convolutional Neural Network architecture. More specifically, the Scaled YOLO version 4 is used [12]. The YOLO algorithm can locate and classify multiple occurrences of smoke and fire based on a single "look" at an image, as shown in Figure 6. The temporal analysis is defined by a persistence of 5 minutes of consecutive frames detected with smoke or fire as show in Figure 4. The proposed detection system consists of two tasks performed sequentially as show in Figure 5: detection (artificial intelligence) and tracking (temporal analysis). The first task aims to identify the occurrences of fire and/or smoke in the scene. For this purpose, an object detector based on a 2D CNN is used. The tracking task, in turn, has a supplementary role. It takes the detections made in the previous step and tries to verify if the detected object is in fact fire or smoke based on its temporal behavior along the incoming frames. If the event is confirmed, an alarm is triggered. The integration of the detector with the tracker allows not only to identify fires or smokes with greater reliability, but also to determine its proportions and, consequently, to estimate the efforts required to fight it.



(a) (b)

Figure 4 The basic blocks of algorithms developed: a) oriented to characteristic extraction, b) black box (using AI) and temporal analysis

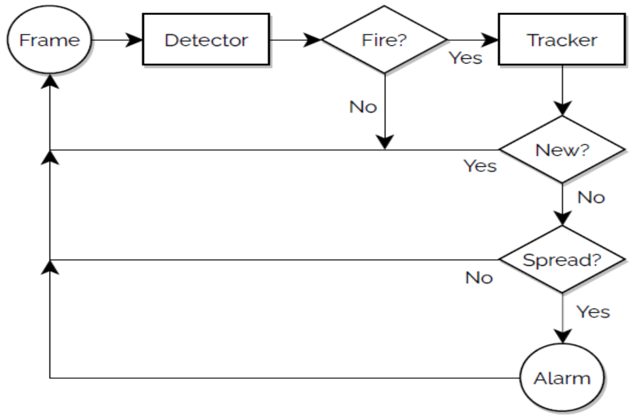


Figure 5 *Closer look at detection and tracking of temporal analysis combined with AI*.

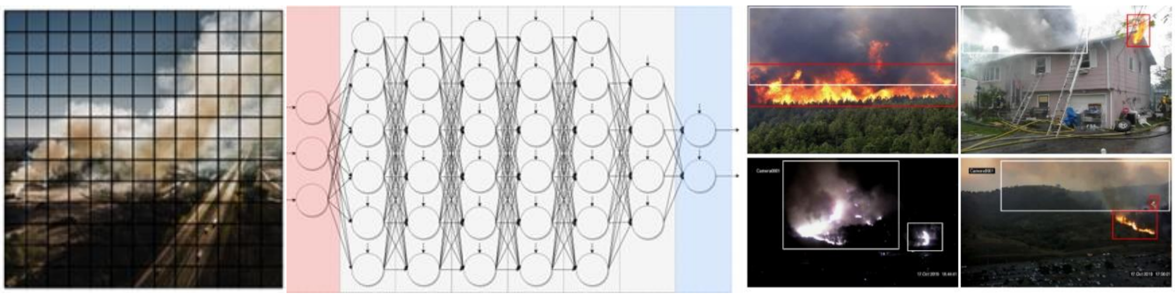


Figure 6 *The representation of basic blocks of algorithms developed for WEB processing.*

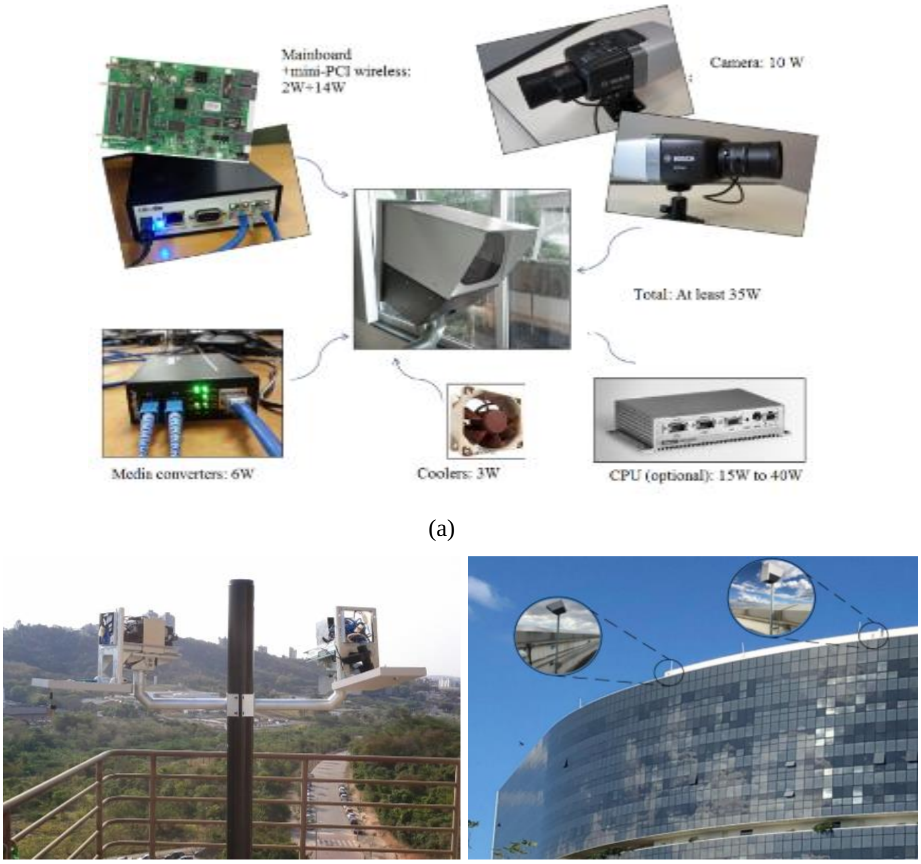
3 THE PERFORMED PROCESSING VIDEO

The detection framework shown in Figure 4 (b) works well when processing video from a single camera. However, as the project grows, the number of cameras used for monitoring increases: at the time of writing this paper, there are 11 cameras in the system. Processing video from multiple cameras is not a trivial task, especially when we consider the complexity of the Yolo algorithm and the high computational resources it requires. Thus, we need a software architecture that can handle video streams from multiple cameras that enables scaling as the number of cameras grows to hundreds or even thousands. To achieve this, we have developed an asynchronous version of the detection system based on parallel computing. The current implementation is based on multi-threading. However, this can be easily expanded to a distributed computing architecture, with the various computing nodes spread over different machines connected over the Internet. This also increases the scalability of the system, as the number of machines can be increased as the number of cameras in the system increases.

This architecture is not only appropriate for the case where the detection algorithm runs on a multi-core machine but can also be implemented on a multi-machine setup (computer cluster). This opens the possibility of running our detector on a network of low-end computing hardware (e.g., Raspberry Pi), where each device is responsible for a single camera. The artificial intelligence trained with over 30 thousand labeled images has achieved a mean average precision (mAP) of over 80%. It is more precise for smoke detection due to the more subjective labeling of fire (e.g. sometimes it is hard to define whether labeling two fire clusters in a single box or one box for each fire cluster). Using a server with high-end graphics processing unit (GPU), over 35 frames can be processed per second in a single instance of the neural network. Considering that the GPU memory can store up to 2 instances, the processing rate can be as high as 70 frames per second. The time response of the system is not much constraining, so that 2 frames per second is more than enough to analyze from a single camera. Hence, a single server can support over 35 cameras. The persistence of 5 minutes has decreased the rate of false alarms to less than 2 per month. The previous persistence of 30 seconds leaded to a rate of over 10 false alarms per day. The loss in time response is relatively small in practice compared to its gain in accuracy.

4 THE PERFORMED HARDWARES IN PILOTS PROJECTS

A pilot project, with all the infrastructure that can be used, was carried out for tests in real environments. For that, the following equipment was used: 2 routers (mainboard + mini-PCI wireless card), two cameras, two media converters, 4 coolers, and a computer with x86 CPU, as shown in Figure 7 (a). The power consumption is one of the complicating points of installation in areas with difficult access, requiring at least 35W in the current configuration. For this reason, the two pilot prototypes for model shown at Figure 4 (a and b) were installed as shown in Figure 7 (b) and Figure 7 (c). In these places the supply of electric energy and internet access are available, and the camera views are towards vegetation landscapes. The same sites remain operational until today, with video streams feeding new version of algorithm shown in Figure 4(b) and Figure 5.



(a)

(b) (c)

Figure 7 – Set of equipment used in first pilot tests: (a, b) BHTec site, focus on UFMG´s forest, c) Serra Verde State Park site, view is possible through cameras installed in MG Governor´s Building, 138 kV power plant is nearby.

4.1 Sharing cameras from other sites

It is possible to include third-owner cameras into the system, in order to reduce investment in new installation of hardware. In this project, Rola Moça State Park "RMSP" showed in Figure 8 (a), that has its own camera system, currently monitoring six forest sites, wirelessly connected in broadband to a local data network, had its camera streams shared through a radio link connecting the park to UFMG´s server that is 16 km away. The automatic fire-smoke detection system provided by IA algorithms at UFMG's server offers a direct integration with RMSP site and personal through internet and mobile devices. The Figure 8 (b) shows an example of the sensitive green area that the camera's infrastructure of the RMSP will bring as benefits to all stakeholders involved, in addition to enabling increased coverage by expanding the camera system with a sharing infrastructure, as shows PTZ camera in Figure 8 (c and d). The scope of project is not using commercially available satellite imagery because the delay of all spectrums available. The detection smoke and fire has to be faster analyzed by digital camera than delay of available satellite imagery.

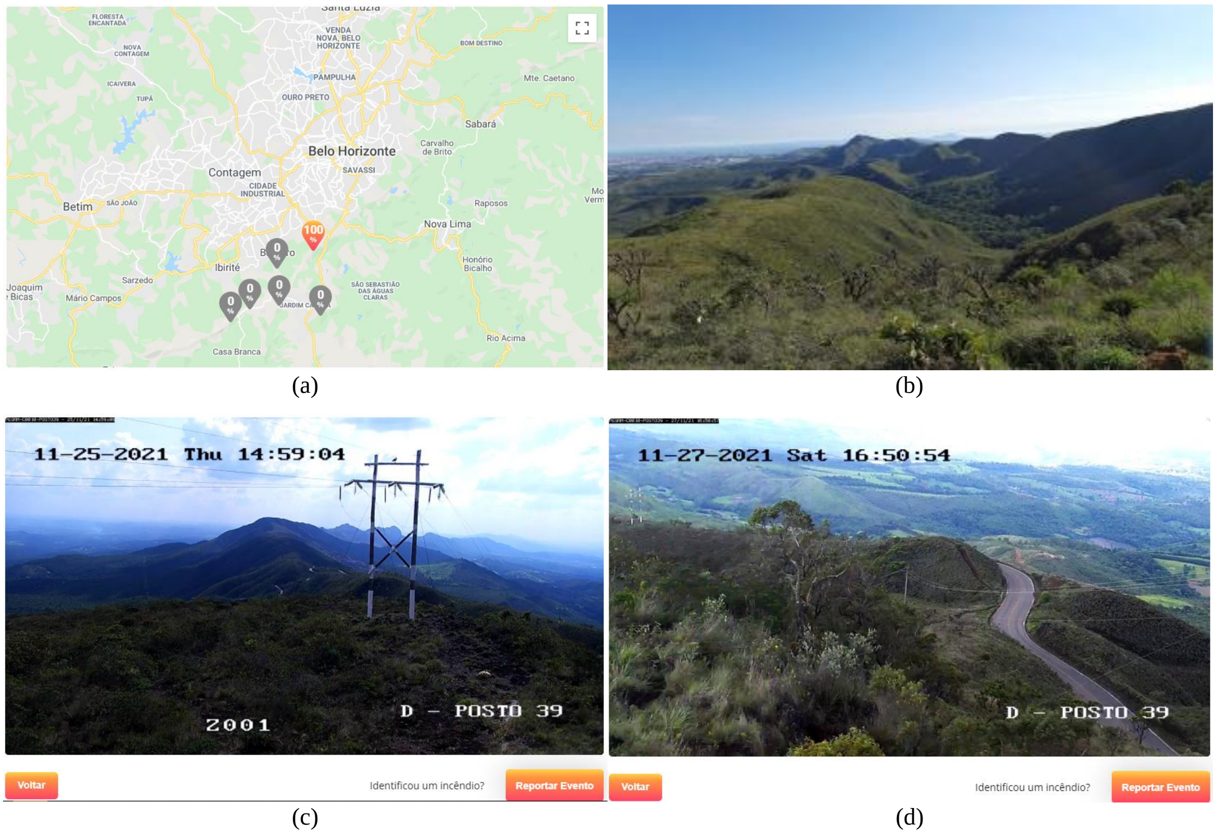


Figure 8 – a) Google map of Rola Moca State Park around Belo Horizonte City, b) local vegetation, c) posto-39 site near 69 kV Lines, d) PTZ camera movement of 39 site.

The process of sharing infrastructure until now is being carried out through technological cooperation agreements between the stakeholder involved in the project. No business model for commercial exploitation of this technology has yet been defined. But what is happening experimentally is the shared use of smoke and fire detection IA algorithms on a server with several sites sending images over the internet. Each stakeholder involved has the responsibility to keep its infrastructure in operation. This technique can not replace direct interaction with all stakeholders involved. The explanatory and educational expenses in wildfire can not be cut off.

4.2 Actual hyperspectral images applied to fire detection tests

The spectral content emitted by fire contains information that goes far beyond the light intensities in the red, green, and blue (RGB) bands, commonly used in image-based fire detection methods. RGB cameras capture visible light in low spectral resolution. The spectral information in visible light is spread-out only in these three large spectral bands. The electromagnetic radiation spectrum of fire covers not only the visible light (VIS) but also the infrared (IR) range. A more detailed spectral analysis can be done by dividing the light spectrum into a larger number (tens or even hundreds) of narrow bands, which represents a greater spectral resolution. This allows a spectral signature of the light source to be obtained. In this context, the fire electromagnetic radiation emitted by the burning material produces a unique spectral signature, which allows its detection and classification. Hyperspectral cameras capture the spectrum of light in the visible and near infrared range with high spectral resolution and thus provide these spectral signatures. The Figure 9 illustrates a fire image captured by a SPECIM FX-10 hyperspectral camera (224 spectral bands with an average width of 2.68 nm) in RGB format (rendered) and an image associated with the 769.6 nm band (rendered). The Figure 10 (a) shows a set of monochromatic images at different wavelengths in both visible (VIS) and near-infrared (NIR) ranges. The Figure 10 (b) shows the spectral signature of a pixel in the fire region of the image. It is expected to reduce fire detection error with more detailed spectral information.

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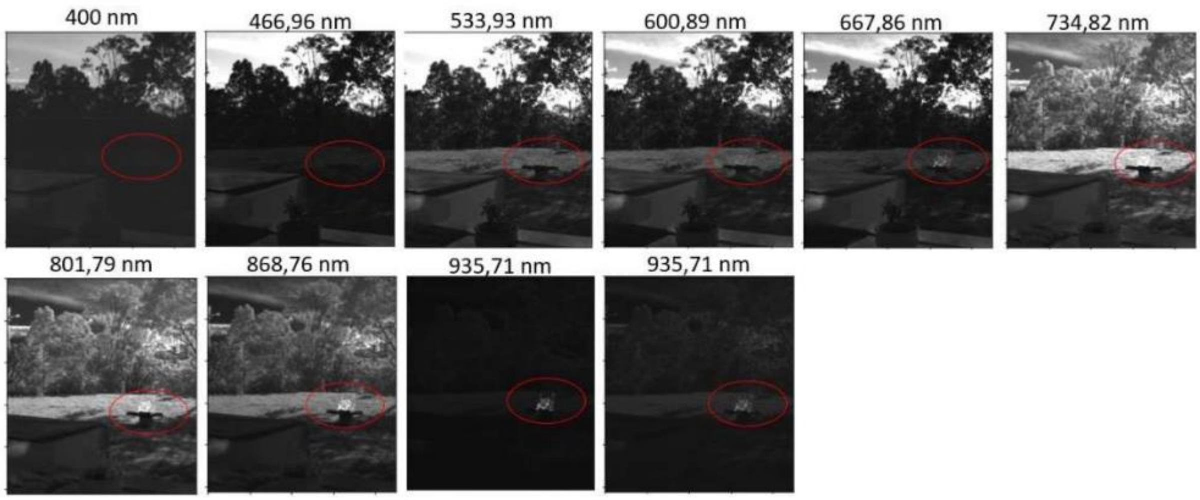
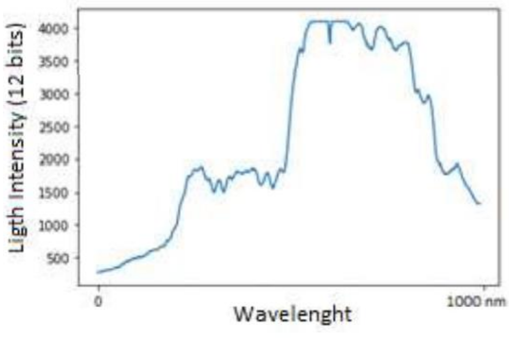
(a) (b)

Figure 9 – Fire image captured by a SPECIM FX-10 Hyperspectral camera: a) RGB rendering of an initial fire focus scene; b) hyperspectral look at 769,6±1,3 nm wavelength makes fire easier to detect.



(a)



(b)

Figure 10 – a) Monochromatic images at different wavelengths (VIS and NIR), b) Spectral signature of a pixel in the fire region.

However, nowadays, it is still not possible to use hyperspectral cameras on a large scale, either due to their high price or because of the need to carry out specific configurations for each measurement. A possible alternative is to use a database that contains hyperspectral images and the corresponding RGB images to train a neural network (or other artificial intelligence system) to infer the hyperspectral content of an image from the RGB information captured by a low-cost camera. Efforts in this direction are being carried out with promising preliminary results.

5 THE PERFORMED WEBPAGE PROJECTS

The first website-intranet application was created with the aim of promoting the interaction between developers only and the trial computer vision system. Through the website-intranet access the cameras provided streams to fire-smoke characteristics-based algorithms that generated alarms manually confirmed/rejected, which helped researchers learn about the problem in real conditions. Figure 11 (a) shows the intranet website in corporate Cemig´s network. In Figure 11 (b) the region with the red rectangle indicating the scene in which first real scene smoke was detected. The smoke and fire's focus were located approximately 3 km from camera’s location, making it a very complex situation to test the system. It is a region surrounded by a large amount of green areas, including a great view of the Federal University of Minas Gerais campus, where the algorithms of smoke and fire detection were developed.

The second and third version of website & APP applications have been created with the aim of promoting the interaction between web society and the computer vision system. Through the website, web users can access the cameras and generate manual or just confirm alarms that help them improve machine learning into system detections. In Figure 12 shows the currently sites at two Forest Parks of Belo Horizonte city. Figure 12 (a and b) shows an interesting view of night and day of Belo Horizonte City from Rola Moça State Park site. The Figure 12 (c) shows a sensitive green view of Serra Verde State Park near Cemig’s 138kV substation and OHL complex from cameras at MG Governor´s Building.

(a) (b)

Figure 11 (a) Image of the cameras in the Cemig´s intranet, (b) Result of an actual smoke detection that occurred during the pilot test. The upper left red rectangle indicates region in forest near 13.8 kV Distribution Network where the smoke was located.

(a) (b) (c)

Figure 12 – Image from one site in Rola Moça State Park with view of Belo Horizonte City at a) night and b) day, c) Park Serra Verde near 138 kV Cemig´s substation and OHL complex.

The experiences of the users were obtained by Design Thinking methodology applying in a set of voluntary web users to define requirements on the third version of website & APP applications. Since 2012 this project has been receiving unrestricted support from several institutions, public and private, which voluntarily collaborated through the web society despite it has being a R&D project yet. The intuitive increase the number of volunteers users is focus on companies interested in environmental protection, schools, universities, public authorities responsible for early detection and fighting wildfires.

6 THE EXPERIMENTAL WILDFIRE DETECTION

It is expected to reach 80% accuracy with the increase of the image bank and improvement of training techniques, where such a precision measure considers both false alarms (i.e. false positives) and alarms that should have been generated but were not (i.e. false negatives). The neural network has been adjusted so that it is not difficult to recognize a real wildfire, though this tunning tends to generate more false alarms. Avoiding such false alarms has been a challenge and the most frequent confusions are (i) sun rays, reflections in water, raindrops and fog recognized as smoke and (ii) sunsets and lights detected as fire. Interestingly, some outbreaks of wildfire detected by the neural network would hardly be detected by a human being, which is an indication that the neural network is overcoming the monitoring capacity of human beings. The Figure 13 shows registers of hard situations that the algorithms worked very well.

(a) (b) (c)

Figure 13- Experimental images already obtained in hard situations of detection. a) sunset and fire detection in the same frame, b) smoke and fire detection at night and c) smoke detection with bird movement in front of the camera.

7 FUTURE WORK

The shared infrastructure of cameras and data links should be installed in remote places while preserving connectivity to the internet. The use of OHL assets and sites has the potential to help escalate the observation area across the country land. Thus, the optical fiber that passes through these assets could be used to transport camera streams. In addition, strems could have radio transmission to internet, so that, even if the optical link could not be shared, communication to remote sites is still guaranteed. But the energy supply to camera continues to be hard task to do in such remote places. The use of conventional batteries and photovoltaic panels do not seem to be the ultimate solution in large scale. The Figure 14 (a and b) illustrates the challenge in sharing infrastructure of cameras in complex OHL assets placed into the forests. Then, some financial incentive to Agents of OHT could be implemented in regulations of energy sector in order to make the sharing infrastructure easier. The Figure 14 (c) shows the site of Cemig's Barreiro OHL 345 kV tower built within this project. The fact that the system can use the support of the transmission towers to install the cameras is highlighted but there must be a viable clear view to an internet radio spot where optical fiber isn´t available, and there is no easy power supply for the camera. In order to solve this trouble, the use of Power over Fiber – PoF technology as shown in the Figure 14 (a) is realistic. In time of crisis, there is assurance that the data Utility´s network must be functional, and the website will be accessible for assuring high availability of existing Utility's cameras. For this reason, the project uses private link of internet communications.

Another challenge in detecting fire and smoke is to lower the probability of generating false-alarms. Thus, the strategy of how web voluntary people can interact with new technologies in order to help training neural networks is devised to be an important investment into the continuity of R&D in what concerns to fire and smoke detection. Figure 15 shows some real register of the false alarms detected. Another trouble to be solved is how should the use of video information be assessed for data protection reasons. Vandalism aspects and limitation of PoF energy capabilities and cyber issues for remote cameras installed in tower of OHL must be considered in the design of the infrastructure.

(a) (b) (c)

Figure 14 - Challenging in sharing infrastructure of cameras into OHL assets. a) micro camera with PoF – Power over fiber technology, b) OHT without access into Amazon forest, and c) 345 kV Cemig´s OHL site with off-grid autonomous camera system comprised of PV-battery power supply and radio link to internet.

(a) (b)

(c)

Figure 15- Experimental images already obtained in false-alarm detection: a) spider out of focus in front of camera identified as smoke, b) the vegetation in movement in the orange flowers color, and c) fog view in landscape.

8 CONCLUSION

In this paper, a computer system for environmental monitoring using cameras and computer vision was presented. New algorithms for fire and smoke detection were developed with a computational performance superior to the consolidated methods. Experiments in several videos were carried out consolidating the tested methodologies. The artificial intelligence is a convolutional neural network with an architecture called scaled YOLO version 4 [12] was selected, which can classify and localize multiple occurrences of smoke and fire in a single look at an image. The temporal analysis is defined by a persistence of 5 minutes of consecutive frames detected with smoke or fire. The proposed detection system consists of two tasks performed sequentially as detection and tracking. The website & APP applications have been created with the aim of promoting the interaction between web society and the computer vision system. Through the website, web voluntary users can access the cameras and generate manual or just confirm alarms that help them improve machine learning into system detections. So this paper showed the intangible and innovative efforts to bring the web society collaboration for better acceptance for O&M and construction procedures of OHL with society worried about climate changes.

Monitoring the wildfires using assets of OHL brings the second another important use in addition to supplying electricity only. The infrastructure of cameras accessible via website systems could also be used for other applications, such as monitoring risks of accidents in the power lines or detecting invasion of RoW of OHL. Though, nowadays, it is still not possible to use hyperspectral cameras on a large scale, either due to their high price or because of the need to carry out specific configurations for each measurement, there is an alternative idea that comes around to benefit from such a technology. It is to use a database that contains hyperspectral images and the corresponding RGB images to train a neural network (or other artificial intelligence system) to infer the hyperspectral content of an image from the RGB information captured by a low-cost camera. Efforts in this direction are being carried out with promising preliminary results. This project had a great impact in society covered by the press due to society's attention to burning in conservation areas. This aspect of the project will be further expanded to allow access to cameras with the possibility of generating manual alarms that serve as a database, aimed at updating and improving the proposed methods. This served as validation of field research using society to assist in environmental monitoring in Minas Gerais State supported by sharing of Cemig Utility OHL´s infrastructure. Despite the various advances achieved, there are still several challenges to be overcome, such as improving the accuracy rate (eg with the use of temporal information or other light wavelengths of spectra) and improving user interaction (eg using a mobile phone application for an easier and faster interaction) that is being worked out.

9 ACKNOWLEDGEMENTS

This project (Cemig D383 and D919) was funded by ANEEL (Brazilian Electricity Regulatory Agency). Special thanks to Cemig, UFMG, Gaia, UFVJM, IEF-MG and SEPLAG-MG by the friendly cooperation dedicated to this joint development project.

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