Detecting Wildfires Using Unmanned Aerial Vehicle with Near Infrared Optical Imaging Sensor

Edwin Magidimisha
Optronic Sensor systems, Defence and Security,
Council for Scientific and Industrial Research
Pretoria, Country
e-mail: EMagidimisha@csir.co.za

Zimbini Faniso-Mnyaka
Optronic Sensor systems, Defence and Security,
Council for Scientific and Industrial Research
Pretoria, Country
e-mail: ZFaniso@csir.co.za

Seelen Naidoo
Optronic Sensor systems, Defence and Security,
Council for Scientific and Industrial Research
Pretoria, Country
e-mail: SNaidoo@csir.co.za

Muhammad Nana
Optronic Sensor systems, Defence and Security,
Council for Scientific and Industrial Research
Pretoria, Country
mnana@csir.co.za

***Abstract*— The severity of wildland vegetation fires is expected to grow in response to climate change. Therefore, the price of combating fires will likewise go up while still posing a serious risk to the firefighters. Various countries have invested enormous sums of money in combating fires throughout the years, and this trend is expected to continue. This provides compelling reasons for surveillance systems that can track and detect wildfires at early stages. The Optronic Sensor Systems of the Council for Scientific and Industrial Research (CSIR) in South Africa is developing a small, cost-effective Near-Infrared (NIR) optical imaging payload for tactical forest fire-fighting operations. This paper reports on the field measurement from sensors that detect NIR spectral emissions from the electronically exited alkali metal Potassium (K) emitted during the flaming phase of the biomass. The NIR sensor consists of a combination of two optical imaging systems (target and reference sensor) placed side-by-side with common (identical) field of view. The concept uses images obtained from the optical imaging systems are compared to determine the pixels which are much brighter in the target band relative to the reference band, which are defined as fire detections. This principle uses a portable imaging system consisting of two similar complementary metal oxide semiconductor (CMOS) cameras with high sensitivity within the NIR band. The fire detection is computed using the K-line ratio algorithm. The results presented in this paper show that it is possible to perform early fire detection of biomass fires using low cost NIR sensors coupled with advanced image processing algorithms.**

Keywords-Potassium: Near-infrared, Unmanned Aerial Vehicle; Wildfire, K-line, CMOS.

I. INTRODUCTION

The global incidence and severity of wildfires is expected to rise in response to climate change [1, 2, 3]. These wildfires incidents further exacerbate climate change due to CO2 and black aerosols emission This serves as a strong motive toward development of optical surveillance systems that that can detect and monitor wildfires. These can be applied on terrestrial, airborne and space platforms. There are various reports that show the use of spectrometers to detect vegetation fires within the near infrared. The utilization of the NIR band for the detection of K spectral emission from burning vegetation fires was demonstrated using the airborne AVIRIS data [13]. Vegetation fires have strong signatures with strong emission lines of potassium (K) at 766.5 nm and 769.9 nm. The Council for Scientific and Industrial Research (CSIR) developed a near infra-red (NIR) sensor prototype for the detection of alkali metal Potassium (K) emitted during wild land vegetation fires at an early stage. The optical system was integrated into and operated from an unmanned aerial vehicle (UAV) using remote sensing techniques. Recent years have seen great progress in the field of using unmanned aerial vehicles for forest fire monitoring, detection and even fighting [17]. The integration of UAVs with remote sensing techniques is aimed at providing rapid, mobile, and low-cost powerful solutions for various fire tasks [18]. A measurement campaign to test the performance of the sensor was conducted by the Council of Scientific and Industrial Research (CSIR) and was supported by the DSI. The UAV NIR sensor was tested at the Grasslands Flying Club in Centurion, South Africa on 18 March 2022. This paper reports on the results obtained during the field exercise which has the potential to provide a cost-effective solution for early fire detection of wildfires at low altitudes.

II. BACKGROUND

Compared to fixed ground-based wildfire detection systems UAVs can provide a broader and more accurate perception of the fire from above especially in areas that are inaccessible or considered too dangerous for operations by firefighting crews. UAVs can cover wider areas and are flexible, in the sense that they monitor different areas, as needed [5]. UAVs provide eyes above the firefighters and can provide important information on the fire progression. Due to the rapid increase in UAV technology development, the use of this platforms is receiving a lot of attention in the application of forest fire detection. This is due to significant potential in reduction of operational costs compared to other aerial based detection platforms such as manned aircraft.

In 2015 Chi Yuan et al [6] proposed a vision-based UAV mounted system for detecting forest fires. This method uses both motion and chroma characteristics of fire in the decision rules to improve the reliability and accuracy of fire detection. More recently Chi Yuan et al [7], used visual images captured by an optical camera of an unmanned aerial vehicle. Then, two color spaces, namely, RGB and HIS were chosen as inputs of a fuzzy logic rule and an extended Kalman filter was employed to adapt environmental condition variations and to perform smoke detection. Extending the color-based methods in fire flame and smoke, pixels are segmented using both color and motion characteristics [8, 9]. For the estimation of color features, they utilized three color spaces, RGB, YCbCr, and HIS, whereas for the extraction of motion characteristics it was noted that flames have turbulent movement or disordered characteristics.

Thus, an optical flow algorithm was used to examine the motion characteristic of forest fires and extract fire motion pixels using dynamic background analysis. Sudhakar et al. [10] proposed a method for forest fire detection through UAVs equipped with an optical and an infrared camera. They used a LAB color model and a motion-based algorithm followed by a maximally stable extremal regions (MSERs) extraction module. For improved presentation, the extracted forest fire detections are joined with landscape information and meteorological data. Chen et al. [11] used optical and infrared sensors and data to train a CNN first for smoke detection and then for flame detection.

In paper on “Saliency detection and deep learning-based wildfire identification in UAV imagery.” [12], they developed a system consisting of a central station and several aerial vehicles equipped with infrared or visual cameras, aiming to increase the coverage area. For fire detection, they applied a threshold for fire segmentation and then performed color and fire contour analysis.

III. DETECTION PRINCIPLE

An overview of the fire detection system is depicted in the schematic on Figure 1. Images of the burning biomass fire containing the potassium element and signature are captured and recorded by the dual camera system for processing. During the image processing stage, the OSS developed algorithm is applied to the pair of images to determine if a fire has been detected.

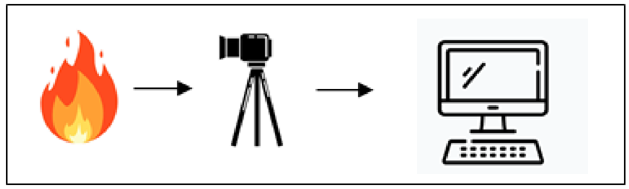


Figure 1: Simplified schematic depicting overview of fire detection system.

A. *The Potassium element*

Potassium belongs to the alkali metal group and is in the first column of the periodic table. It is one of the abundant elements in vegetation species [13, 14]. It has a single valence electron that present unique narrowband spectral emission lines within the visible and near infrared (NIR) wavelength range when vegetation biomass is heated to high temperatures during the process of flaming combustion [15]. The spectral emission of K appears as doublet at 766.5 nm and 769.9 nm spectral bands [16]. With the advancements in filter design, filters can now detect low-level signals while suppressing almost all emissions within the outer band by targeting specific elemental emissions from a source signature. These advancements in technology open the opportunity for the development of compact sensors capable of detecting spectral signatures and can be advanced to compete with other passive sensors operating in other bands. In this project, ultra-narrow band imaging is used for the detection of K furnished on CMOS detectors. The integration of COTS, and ultra-narrow band imaging allows the design of compact and less power-hungry systems which can be easily integrated on a UAV.

B. *Fire detection system*

The NIR fire detection sensor presented in this paper comprise of two optical imaging systems placed side-by-side with common (identical) field of view. These cameras are fitted with ultra-narrow band filters with 1nm bandwidth sensitive at 770 nm referred to as the K-line band, and 757 nm referred to as the reference band. The target and reference channels are temporally synchronised at the electronic level such that pairs of images (one from the target band and the other from reference channel) are obtained at the same instant. Fires are detected by comparing the NIR channel image to the reference channel image. Pixels which are much brighter in the target channel relative to the reference channel are candidate fire detections.

C. *Image Processing Algorithm*

The system image processing begins when two images are captured, one image with K-emission and the other with the background. The images from the two sensors are captured simultaneously. The reference image is resampled to be aligned with the K-line image pixelwise.

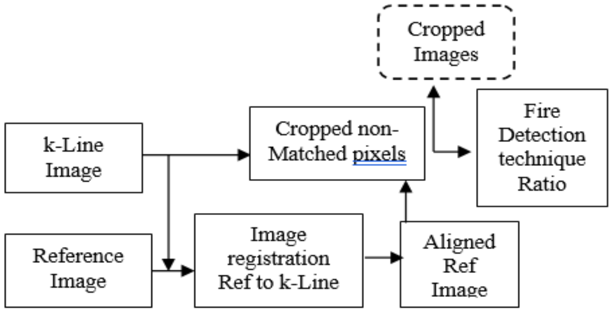


Figure 2: Overview of K-line fire detection principle

The K-line image is not modified in order to preserve the fire front K-line signal emissions. The fire detection algorithm is applied to the matching cropped K-line and reference images. A block diagram giving an overview of the algorithm is illustrated in Figure 2.

IV. METHOD

The field measurements test was conducted at the Grasslands Flying Club in Pretoria West on 18 March 2022. The measurements were done to test the performance of the UAV while airborne. A photograph of the NIR imaging sensor system is shown in Figure 3 during lab testing.

Figure 3: NIR sensor consisting of two cameras side by side furnished with ultra-narrow filters.

The UAV Payload used a development (Raspberry Pi4 8GB) board to control the capturing of images, communication with a ground station, and storage of captured images. The captured images are stored on-board a micro-SD card and are removed after the completion of a sortie. When the memory stick is retrieved and the data is retrieved for archival, it was also inspected while the next mission was executing. Fire detection is performed on a post processing basis by automatically analysing the images stored in the memory card.

The basic UAV payload consists of the following components:

- a processor module with storage,
- the K-line camera payload,
- a viewfinder camera,
- a telemetry radio downlink,
- an analogue video downlink,
- high-definition video downlink,
- a power source, and
- wiring harnesses.

A photograph of the UAV with the payload taken during the design testing phase is shown in Figure 4.

Figure 4: UAV with NIR sensor payload on the DJI 600 drone during a field testing of the sensor.

A deployment to test the new NIR payload aboard an airborne UAV The purpose of the test was to determine whether the new NIR sensor is able to detect ground wildfires from the air at relatively low altitudes (approximately 150m above ground level) and at different aspect angles from the fire. The size of the fire on the ground was approximately 500cm by 500cm.

The following equipment was used during the test:

- M600 UAV with RONIN gimbal provided and piloted by UAV Industries (UAVI),
- UAV NIR payload sensor
- UAV Ground Control Station
- FieldSpec 3 Max Analytical Spectral Device (ASD) with spectral range 350-2500nm
- Weather Station

A. *Atmospheric conditions*

During field measurements the scenario demands that atmospheric computations be made to accommodate the atmospheric effects, caused by molecular absorption and emission (mainly water and carbon dioxide as well as atmospheric scattering processes by aerosols). The atmospheric modelling codes such as MODTRAN,

 ISBN: 978-1-68558-079-7

HITRAN and others can be used to simulate the atmospheric transmission as described below.

A weather station was used to capture the atmospheric conditions measured and the atmospheric transmittance were calculated using the MODTRAN model within the NIR region and is given in Figure 5. Varying the range to higher values increases the gases absorption effects, hence at lower range (~150) some of the absorption lines seem invisible. There is very little absorption effect within the NIR over the 769.89 nm detection band. However, since the region of interest in this study is mostly affected by atmospheric Oxygen, simulated transmission spectrum data was downloaded including Oxygen.

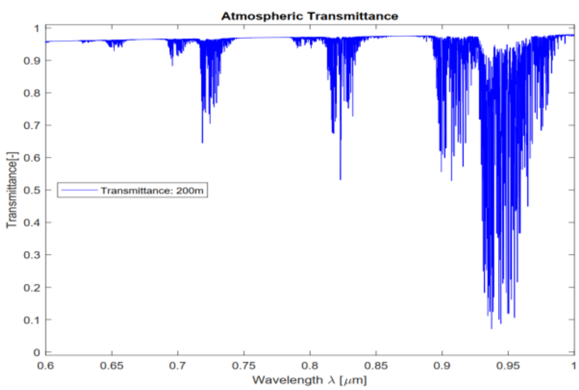


Figure 5: MODTRAN atmospheric model in the NIR region

B. Field UAV measurement

The test consisted of a controlled ground fire using wood and dried grass as the fuel with added potassium (K) as needed to enhance the NIR signature in the fire. An analytical spectral device was setup on the ground close to the fire which is used to record the spectral signature of the fire as it burns. It provides reference spectral data of the fire from the ground for checking whether the NIR signature is contained within the fire. The range at which the detection tests are conducted is approximately 150m from the fire. Two test points of interest applicable and sufficient for proving the initial success of the fire detection system is highlighted in the next section. Figure 6 below gives an illustrative overview of the mission profile used during the fire detection tests.

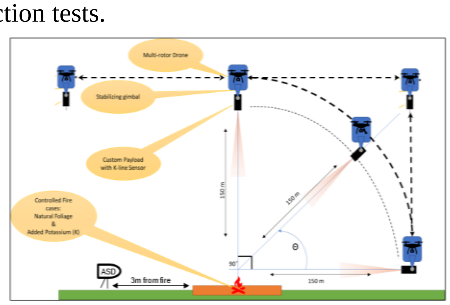


Figure 5: Illustrative overview of flight mission profiles

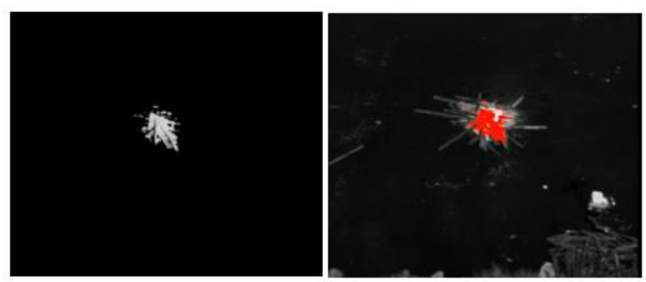
V. Results

Some of the results from the fire detection tests are presented here. These include UAV NIR image sensor data as well as spectral data recorded by the ASD on the ground. Whenever the NIR image sensor data is shown it is as a pair of images with the left hand side showing the reference image and the right hand side as the target image which has the K-line emission signature indicated. This is indicated as a red overlay after image processing has been applied. The black and white target image shows the masking and therefore isolating the K-line signature.

The ASD data is also presented as a pair of images with the left hand side image showing the total spectral image of the fire in the 350 -2500 nm waveband and the right hand side showing the NIR doublet extracted from this spectral data. The various colour lines shown in the total spectral graph indicate the different spectral graphs of the fire at different instances as it burns within a short timeframe (such as during a testpoint recording).

A. Test Point 1:45 Degree Aspect Angle Fire Detection

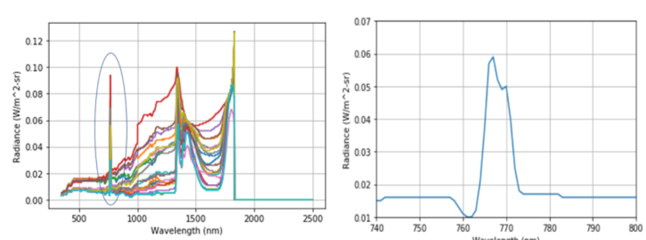
The sensor succeeded in detecting fire from an angle (45° used in this scenario). Figure 6 shows the image of the NIR sensor from the drone perspective. The sensor had full visibility when the fire was recorded.



(a) (b)

Figure 6: NIR sensor images during angular (45°) detection of fire

The NIR signature was fully detected by the ASD sensor as the sensor was fully exposed. The ASD data is given in Figure 7. Several ASD spectral measurements were taken while the UAV was airborne, as shown in Figure 7(a).



(a) (b)

Figure 7: ASD spectral data with NIR zoomed K-line unresolved doublet

Figure 7(b) is the zoomed spectra showing the unresolved K-line doublet due to the ASD resolution.

B. Test Point 2: Directly Above Fire Detection (90° aspect angle)

The sensor succeeded in detecting fire from directly above. Figure 8 shows the images of the NIR sensor. The sensor had full visibility when the fire was recorded. The spectral

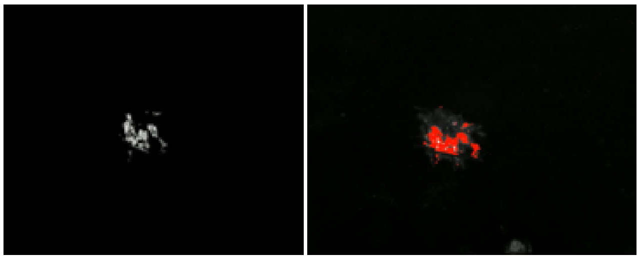
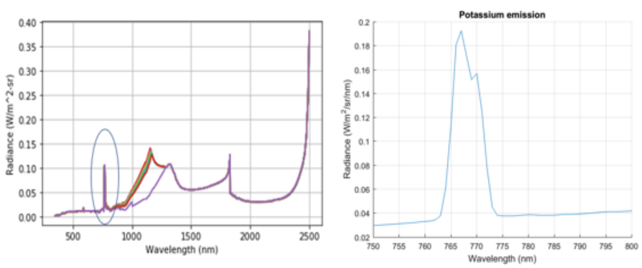


Figure 8: NIR sensor images showing fire detection from directly above

Data logging was a success on the ASD sensor however, the results show that the K-Line doublet signature was not strong (figure 9). This may be due to the fire not burning evenly after more wood was added and the fire was still starting to develop hotter flames with not enough flames at the point where the sensor was pointed.



(a) (b)

Figure 9: ASD data with NIR doublet extracted (b) but not fully detected.

VI. Conclusion

We captured small scale fires using a K-line based fire detection sensor mounted on an unmanned aerial vehicle during a field trial at the Centurion Flying club in Pretoria, South Africa. The results present strong evidence of K-line signature within the vegetation fires detectable using compact CMOS cameras operating within the NIR. The ASD measurement confirmed the spectral location of the K alkali metal present on the vegetation biomass.

This study provides the possibility to perform early fire detection of vegetation biomass using low cost NIR sensors integrated on unmanned aerial vehicles coupled with advanced image processing algorithms. This work is recommended as work in progress to develop system that will not only detect but geo-locate, monitor fire progression, and make evolution estimates of fires in real-time.

Acknowledgment

The Optronic Sensor Systems (OSS) together with all the team members involved in this work, owes thanks to the Aeronautical Sciences Impact Area at the CSIR for the technical assistance provided and to the Department of Science and Innovation (DSI) for their financial support and funding for enabling this research effort.

References

[1] Y. Liu, J.A. Stanturf, and S.L. Goodrick. Trends in global wildfire potential in a changing climate. Forest Ecology and Management, 259(2010):685–697, 2009. http://dx.doi.org/10.1016/j.foreco.2009. 09.002.

[2] Ryan Kelly, Melissa L. Chipman, Philip E. Higuera, Ivanka Stefanova, Linda B. Brubaker, and Feng Sheng Hu. Recent burning of boreal forests exceeds fire regime limits of the past 10,000 years. Proceedings of the National Academy of Sciences, 110(32):13055–13060, 2013. http://dx.doi.org/10.1073/pnas. 1305069110.

[3] Philip E. Dennison, Dar A. Roberts, and Lucy Kammer. Wildfire Detection for Retrieving Fire Temperature from Hyperspectral Data. In ASPRS 2008 Annual Conference, volume 1, pages 139–146, 2008. http: //www.asprs.org/a/publications/proceedings/portland08/0015.pdf

[4] Griffith, D.J., Magidimisha, E., Schloss, Y. and Van Den Bergh, F., 2016. Wildfire Detection using Potassium Spectral Line Emissions.

[5] Panagiotis Barmpoutis, Periklis Papaioannou, Kosmas Dimitropoulos and Nikos Grammalidis. A Review on Early Forest Fire Detection Systems Using Optical Remote Sensing, 11 November 2020.

[6] Chi Yuan, Zhixiang Liu and Youmin Zhang. Vision-based Forest Fire Detection in Aerial Images for Firefighting Using UAVs, 2015.

[7] Yuan, C.; Liu, Z.; Zhang, Y. Learning-based smoke detection for unmanned aerial vehicles applied to forest fire surveillance. J. Intell. Robot. Syst. 2019, 93, 337–349.

[8] Dang-Ngoc, H.; Nguyen-Trung, H. Aerial Forest Fire Surveillance-Evaluation of Forest Fire Detection Model using Aerial Videos. In Proceedings of the 2019 International Conference on Advanced Technologies for Communications (ATC), Hanoi, Vietnam, 17–19 October 2019; pp. 142–148.

[9] Yuan, C.; Liu, Z.; Zhang, Y. Aerial images-based forest fire detection for firefighting using optical remote sensing techniques and unmanned aerial vehicles. J. Intell. Robot. Syst. 2017, 88, 635–654.

[10] Sudhakar, S.; Vijayakumar, V.; Kumar, C.S.; Priya, V.; Ravi, L.; Subramaniyaswamy, V. Unmanned Aerial Vehicle (UAV) based Forest Fire Detection and monitoring for reducing false alarms in forest-fires. Comput. Commun. 2020, 149, 1–16.

[11] Chen, Y.; Zhang, Y.; Xin, J.; Yi, Y.; Liu, D.; Liu, H. A UAV-based Forest Fire Detection Algorithm Using Convolutional Neural Network. In Proceedings of the IEEE 37th Chinese Control Conference,Wuhan, China, 25–27 July 2018; pp. 10305–10310.

[12] Zhao, Y.; Ma, J.; Li, X.; Zhang, J. Saliency detection and deep learning-based wildfire identification in UAV imagery. Sensors 2018, 18, 712.

[13] Vodacek, A., Kremens, R. L., Fordham, A. J., Vangorden, S. C., Luisi, D., Shott, J. R., &Latham, D. J. Remote optical detection of biomass burning using a potassium emission signature. International Journal of Remote Sensing, 23(3), 721−2726, 2002.

[14] Nist Atomic Spectral Database (2001). URL.http://Physics.nist.gov.

[15] S.Amici, M.J. Wooster, and A. Piscini. Multi-resolution spectral analysis of wildfire potassium emission signatures using laboratory, airborne and spaceborne remote sensing, 2011.

[16] Latham, D., 1998, Near-infrared spectral lines in natural !res. Proceedings of the III International Conference on Forest Fire Research/14th Conference on Fire and Forest Meteorology, 16–20 November 1998 (Coimbra, Portugal: ADAI), pp. 513–515.

 ISBN: 978-1-68558-079-7

[17] V. Ambrosia and T. Zajkowski, “Selection of Appropriate Class UAS/Sensors to Support Fire Monitoring: Experiences in the United States,” in Handbook of Unmanned Aerial Vehicles, Springer Netherlands, 2015, pp. 2723–2754

[18] L. Merino, J. Martínez de Dios, and A. Ollero, “Cooperative Unmanned Aerial Systems for Fire Detection, Monitoring, and Extinguishing”, in Handbook of Unmanned Aerial Vehicles, Springer Netherlands, 2015, pp. pp. 2693–2722.