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

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***Abstract*— The increasing severity of wildland fires, largely driven by the effects of climate change, poses a significant risk to both firefighters and ecosystems, while also driving up the cost of combating such fires. Therefore, there is a pressing need for surveillance systems that can detect and track wildfires at an early stage. While traditional methods such as infrared sensors on elevated platforms and surveillance from aircraft have been proven to work in many areas, they have limitations in terms of field of view and cost-effectiveness in covering larger areas. To address these challenges, the Council for Scientific and Industrial Research (CSIR) in South Africa is developing a novel solution for tactical forest firefighting operations. The system takes advantage of the near-infrared (NIR) optical imaging by detecting wildland vegetation fires in the NIR region with cost-effective complementary metal-oxide-semiconductor (CMOS) sensors equipped with ultra-narrow band filters. This approach uses a ratio algorithm on the captured images from two bands to identify pixels with raised intensities that are indicative of a fire. The system is designed to be portable, smaller in size, and can be mounted on an unmanned aerial vehicle to provide real-time support to firefighters. This innovative approach has the potential to significantly improve the speed and accuracy of fire detection in areas where traditional methods are not feasible or effective, such as remote or inaccessible locations.**

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

I. INTRODUCTION

Wildland vegetation fire prevention, detection, monitoring, and suppression are key economic and public safety concerns in many parts of the world [1]. The global incidence and severity of wildfires are expected to rise in response to climate change [2, 3, 4]. These wildfire incidents further exacerbate climate change due to CO2 and black aerosols emission. This serves as a strong motivation for the development of optical surveillance systems that can detect and monitor wildfires. Classical remote sensing of vegetation fires has been through the Planckian emission at the Medium Wave Infrared (3-5 µm, MWIR) and the Long Wave Infrared (LWIR) band of the electromagnetic spectrum [5,6,7]. The Short Wave (1 – 2.5µm, SWIR) infrared band was exploited and deployed on AVIRIS platform [8]. However, the IR band can be mostly affected by other heat emitting sources which could act as false alarms [9].

With the advancement of imaging sensors and filter technologies, there is now increased availability of reliable optical commercial-off-the-shelf (COTS) products at affordable cost. The new sensor technologies such as high-resolution CCD and CMOS sensors, provide an opportunity to enhance wildfire detection, monitoring, and reporting. This study presents a compact and cost-effective method of detecting wildland fires using near-infrared (NIR) spectral line emissions from electronically excited Potassium (K) atoms at 766.5 and 769.9 nm, during biomass burning [10,16, 18, 19]. The Potassium spectral lines can be discriminated against any other background by detector systems that are less costly than the longer wavelength, actively cooled instruments more typically used in EO-based active fire studies [11]. Similarly, new airborne sensor platforms, particularly small, unmanned aircraft, or drones, are enabling new applications for airborne fire sensing [12]. The current study integrates the NIR optical payload onto and operates it from an unmanned aerial vehicle (UAV) using remote sensing techniques.

II. BACKGROUND

In recent years, we have seen great progress in the use of unmanned aerial vehicles with advanced software for forest fire monitoring, detection, and firefighting. The integration of UAVs with remote sensing techniques is aimed at providing rapid, mobile, and low-cost powerful solutions for various fire tasks [12]. Direct forest fire detection by firefighting agencies, as opposed to reports from the public, is typically performed by some combination of fixed detection platforms such as watch towers, aerial detection patrols, and satellite imagery [11]. However, highly elevated platforms are not well suited in area coverage and can result into some areas developing fires unnoticed. Although aircrafts are considered efficient in firefighting, they are expensive to keep airborne for constant monitoring. 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. During firefighting, UAVs provide eyes from above and can provide important information on the fire progression.

A vision-based UAV mounted system for detecting forest fires that uses both motion and chroma characteristics of fire in the decision rules to improve the reliability and accuracy of fire detection was proposed [13]. Sudhakar et al. [14] proposed a method for forest fire detection through UAVs equipped with an optical and an infrared camera using 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 were joined with landscape information and meteorological data. Chen et al. [15] used optical and infrared sensors data to train a CNN first for smoke detection and then for fire flame detection.

III. DETECTION PRINCIPLE

Figure 1 below, illustrates a comprehensive outline of the fire detection system. The system incorporates a dual camera to capture and record images of burning biomass fire, specifically vegetation fires containing the Potassium element signature. The captured images are processed using the OSS developed algorithm that is applied during the image processing stage to analyze the pair of images and establish whether a fire has been detected.

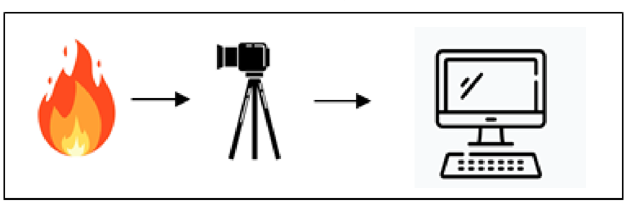

Figure 1: Simplified schematic depicting overview of fire detection system.

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 [16, 17]. 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 [18]. The spectral emission of K appears as doublet at 766.5 nm and 769.9 nm spectral bands [19]. 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 narrow spectral lines 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 using 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 769.9 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. This is done by feature mapping, using a Lucas-Kanada optical flow algorithm [20]. The sections of the individual images that are not common in both are then cropped out, leaving two images of the exact same scene.

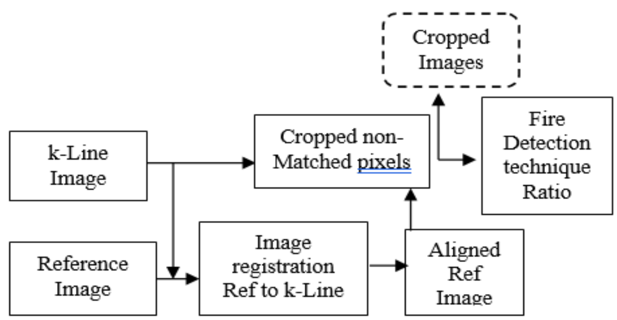

Figure 2: Overview of K-line fire detection principle

The images are not modified with any image enhancement algorithms and are not compressed to preserve the fire front K-line signal emissions. The fire detection algorithm is applied to the matched cropped K-line and reference images. The fire detection is done using the image ratio technique [16, 21]. A block diagram giving an overview of the algorithm is illustrated in Figure 2. The image ratio technique is simple and is implemented as follows:

a) Compute the ratio image i.e., the K-line image divided by the reference image.
b) Compute the global mean and variance of the ratio image.
c) Compute the pixel variance for each pixel in the ratio image.
d) If the variance of a pixel is greater than the global variance multiplied by a user defined sensitivity integer value, the pixel gets classified as a fire pixel. Otherwise, the pixel is classified as a non-fire pixel.

IV. METHOD

The field measurements test was conducted at the Grasslands Flying Club in Pretoria West on the 18th of March 2022. The purpose of the test was to evaluate the aerial performance of the NIR fire detection sensor onboard the UAV. Figure 3 displays a photograph of the NIR imaging sensor system during its lab testing phase.

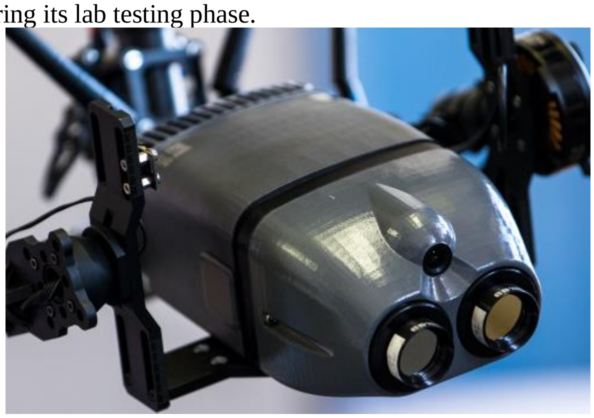

Figure 3: A closer look at the NIR sensor with two CMOS optical sensors placed side by side and furnished with ultra-narrow filters.

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 were stored on-board a micro-SD card and removed after the completion of a sortie. When the memory stick is retrieved and the data is retrieved for archival, the data was also inspected while the next mission was ongoing. Fire detection is performed on a post processing basis by automatically analysing the images stored in the memory card. The basic NIR sensor 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.

Figure 4 shows the NIR fire detection payload onboard the UAV taken during the deployment experiment at the Grasslands Flying Club.

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

Several sorties where carried 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 can 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, HITRAN and others can be used to simulate the atmospheric transmission as described below.

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The atmospheric transmission was calculated using the HITRAN Radiation Transfer Model (RTM) in the NIR region, as shown in Figure 5. The HITRAN data downloaded were in vacuum scale and converted to air using the Elden equation (NIST). The following parameters were used: 20°C air temperature, 101325pa air pressure and 50% humidity percentage [17]. The red lines show the Potassium doublet at 766.48nm and 769.89nm. The 766.48 is absorbed by atmospheric Oxygen as it is located at the Oxygen absorption line and therefore cannot be detected. The K emission lines are within the range of the sequence of the atmospheric absorption lines that peak at about762 nm [22].

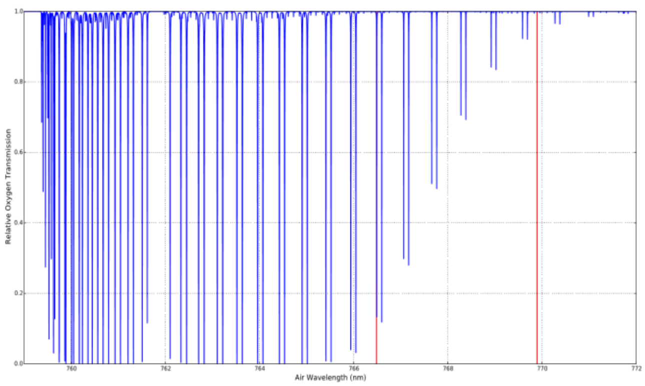


Figure 5: The high spectral resolution Oxygen atmospheric transmittance near the wavelength location of the two Potassium emission spectral lines, data from HiTRAN (http://hitran.iao.ru).

The positions of the K-lines are indicated by two vertical red lines and the deep lines shows the absorption effects arising from the atmospheric absorption gases.

B. Field UAV measurement

The test consisted of a controlled ground fire using wood and dried grass as the fuel. An analytical spectral device was setup on the ground close to the fire (approximately 3m) 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.

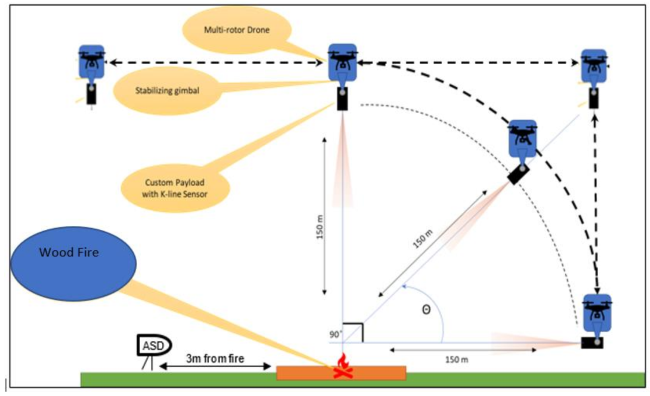


Figure 6: Illustrative overview of flight mission profiles

V. Results

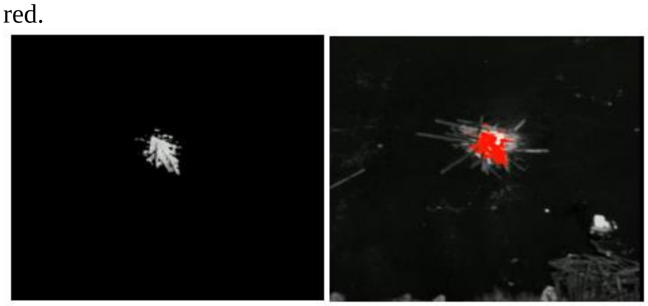
Some of the results from the fire detection tests are presented here. These include UAV NIR image sensor data as well as spectral data recorded by the ASD on the ground. Whenever the NIR image sensor results are shown, they are shown in pairs. The left image is a masked image and the right-hand side is the target image which has the K-line emission signature. The K-line signature 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 FieldSpec 3 spectroradiometer 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 spectral band. The right-hand side shows the zoomed unresolved K-line doublet. 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). The emission spectrum of the fire is clearly visible with spectral radiance generally increasing with wavelength.

Various flight profiles were flown as shared below.

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

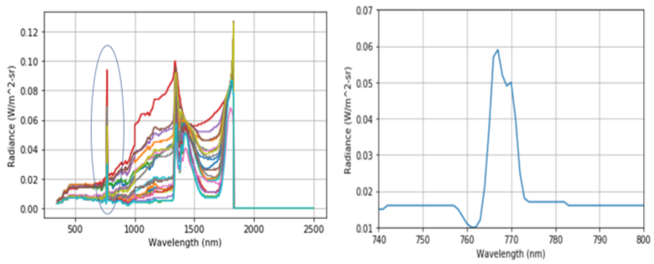
The sensor was able to detect fire from an angle (in this scenario the angle 45° is used). The images were captured while the drone was at 45° as shown in Figure 6. Figure 7 (a) is the masked image of the K-line emission from the fire while 7 (b) shows the unmasked image with K-line painted in red.



(a) (b)

Figure 7: NIR sensor images during angular (45°) detection of fire

The NIR signature was fully detected by the ASD spectral sensor as it was placed close to the scene of the fire. The ASD data is given in Figure 8 below. Multiple ASD spectral measurements were taken while the UAV was airborne, as shown in Figure 8(a) and 8(b).



(a) (b)

Figure 8: ASD spectral data with NIR zoomed K-line unresolved doublet. The figure shows the spectral radiance of the fire within the NIR region.

Figure 8(b) is the zoomed spectra showing the unresolved K-line doublet due to the low ASD resolution of 3nm.

B. Test Point 2: Flying directly Above the Fire (90° aspect angle)

The sensor was able to detect fire from directly above as shown in Figure 9. The figure shows the NIR images as detected by the K-line band.

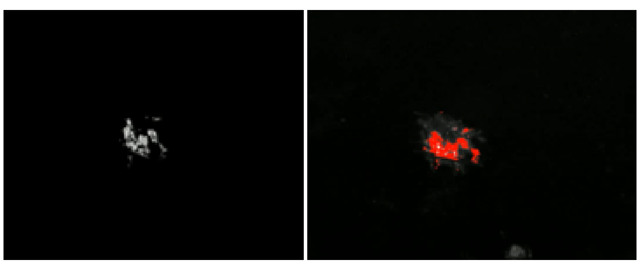
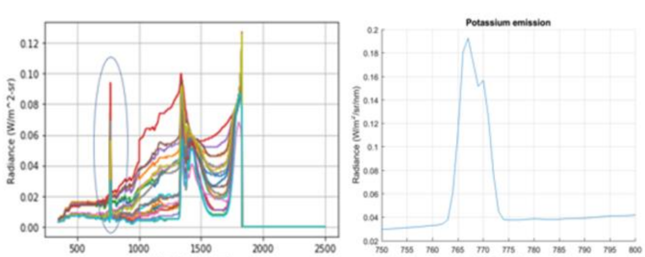


Figure 9: NIR sensor images showing fire detection from directly above

Data logging was a success on the ASD sensor however, the results show that the K-line signature was not strong (figure 10). This is suspected to be because the fire was not burning strong after adding more wood.



(a) (b)

Figure 10: ASD data with NIR doublet extracted (b) unresolved K-line doublet.

VI. Conclusion

Small scale fires were captured using a K-line based fire detection sensor mounted on an unmanned aerial vehicle during a field trial at the Centurion Flying club, Pretoria, South Africa. Results present strong evidence of K-line signature within the vegetation fires detectable by 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.

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