Wildfire prevention through the use of computer vision on UAV

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***Abstract*—Fires are becoming a real problematic all over the world as a consequence of global warming. Satellite platforms are the main tool to monitor and prevent wildfires, even though this method represents a major problem as it is expensive and time consuming.**
An additional challenge for the current monitoring methods is the complex threshold generated by the closeness between buildings, vegetation and dirt. A primary method to differentiate each is through the Normalized Difference Vegetation Index (NDVI) which uses the chlorophyll response of decaying mass as a measurable signal.
This paper focuses on the above mentioned problems to provide a suitable and accurate alternative. The implementation of multiple indices involving five bands of an infrared camera along a thermal camera, together with a genetic programming model was used to replace the NDVI. For the monitoring device, an Unmanned Aircraft System with an attached multi spectral camera was used. The combined design offered high quality and spatial resolution images from low operating altitudes, which resulted in a high accuracy to identify objects at different levels of land degradation. The solution also proved to require less time investment to be implemented.

[1]

***Index Terms*—solar radiation, electromagnetic spectrum, remote sensing, multi-spectral images, genetic programming, vegetation indices, ROS, HOG, SVM**

I. Introduction

Wildfires constitute one of the major hazards against the environment as they have become bigger, more frequent and tend to spread into new areas, impacting land that previously did not burn [1]. This contributes to more aggressive climate change effects and the endangerment of different species of plants around the globe [2].
It is hard to find the origin of the wildfire as they are caused randomly by humans or nature itself, for example a campfire that is not fully extinguished or a lighting during a thunderstorm can cause a wildfire. Their behaviour is also unpredictable and the spreading depends on several weather conditions, such as wind speed and moisture. In the past, watchtowers and piloted fire observation airplanes were used to detect wildfires, even though they were costly, time consuming and dangerous. The key missing aspect of all previous methods is the lack of real time recognition and forecast of wildfires that could give emergency services an upper hand on controlling the wildfire [3].
Unmanned Aerial Vehicles (UAV's) provide an aerial view in large-scale wildfire to emergency services so that they can monitor and provide quick response to control the fire. Previously developed methods mostly revolve around the algorithm in which reflected sunlight form fire is extracted using color and motion characteristics. The extracted features are then processed by an installed computer on a UAV as described in [3] and [4]. The success rate of fire detection using UAV's and Neural Networks is very high as compared to other conventional methods.
The design described in this paper consists of two major parts, wildfire prevention and detection. For preventing the fire a genetic programming model is used to detect environmental factors that can cause a fire to start. Humans are also agents for causing fires because they bring bottles and reflective material into environments. A supervised learning method SVM (Support Vector Machine) together with a HOG (Histogram of Oriented Gradients) is used to recognize humans in the frame.
The main fuel for fire generation and spreading in a forest are plants. It is more likely that a fire will start from a decaying vegetation and will spread more to the area covered by it. So in order to detect this dead vegetation an index NDVI is used. NDVI is an indicator of vegetation greenness and is also used to tell the presence of live green vegetation in a plant. Finally for detection, a fire detection method is constructed using RGB images from the camera.
The implementation of these algorithms took place in two stages, online and offline. The genetic programming algorithm and HOG/SVM have a learning step that must be completed prior to on boarding the UAV due to their nature.

II. Vegetation Indices

A Vegetation Index is a single number obtained by converting observations from many spectral bands into a single value. It's used to emphasize the presence of green, vegetation features in an image, making it easier to differentiate them from other things in the scene. Various characteristics of the

[1]Contributions:
Nouman : Abstract, Online Procedure and Results and discussion
Daniel: Vegetation Indices, Online, offline and Results
Jeroen: Introduction and Conclusion

plant cover in the image can be evaluated depending on the transformation method and spectral bands employed, such as the percentage of vegetation cover, amount of chlorophyll content, leaf area index, water content and so forth. The bands of the spectral light that were used are shown in the Table 1, for the graphical representation refer to Annex 1 Figure 6.

TABLE I
SPECTRAL BANDS USED

Name	Center Band	Bandwidth
Blue	475nm	20nm
Green	560nm	20nm
Red	668nm	10nm
Red edge	717nm	10nm
Near infrared	840nm	40nm
Thermal	10500nm	6000nm

Using the mentioned bands, the vegetation indices calculated on the project are shown in the Table 2 along with its characteristics.

TABLE II
SPECTRAL BANDS USED

Name	Characteristics
NDVI	Highlights live green vegetation.
PRI	Sensitive to vegetation productivity and stress.
DVI	Distinguishes between soil and vegetation.
GARI	Sensitive to a wide range of chlorophyll concentrations.
NDWI	Monitor changes in water content of leaves.
EVI	Similar to NDVI but is more responsive to canopy structural variation. It has an improved sensitivity in high biomass regions.
SR	Measure of the light-use efficiency of foliage. Indicator of water stress and CO2 uptake by plants.

The vegetation indicators are crucial input for genetic programming in both the offline and online sections, as the generated code will have the parts of both tree and leaves.

III. OFFLINE PROCEDURE

Two distinct procedures will be covered in this section.The first one will be genetic programming and the criteria used to create database. The second one will be detection of pedestrians.

A. Image acquisition

Environmental and atmospheric factors change the light intensity of an area, resulting in variations in the saturation of the captured images. Thus, before any flight, a radiometric calibration was done in order to perform multiple flights on different dates. Four flights were conducted and six different data sets of images were acquired, one for each band.

B. Geometric Corrections

Because of the geometric distribution of the camera's foci, a geometric translation had to be made on all but one of the foci pictures. The translation matrices were computed using SURF (Speeded Up Robust Features), a technique for detecting characteristic points between two images. This procedure was carried out for images corresponding to the Red, Green, Blue, NIR and Thermal bands in relation to the RedEdge band which was physically in the center.

C. Genetic Programming

Aerial photographs can capture a wide range of diverse elements. Vegetation, buildings, soil, human-made things, water, rocks and a lot more things. However, the emphasis is on vegetation, specifically decomposing vegetation. All the major elements mentioned above were taken into account to characterize the data set of images. With the use of vegetation indices as inputs, a genetic programming algorithm was built to differentiate decaying vegetation from the other variables.

1) Selection and segmentation: The workspace contained five elements: living vegetation, dead vegetation, soil, buildings, and water. It is necessary to separate the dead vegetation from the others. The numerical result was analyzed in the different vegetation indices, and a numerical closeness was discovered that made distinguishing between dead vegetation, buildings and soil a very difficult task. As a result samples (Figure 1.) were taken from various images containing at least one of the three elements to be further use in the fitness function.

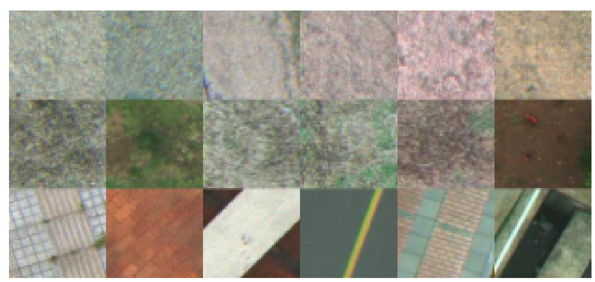

Fig. 1. Matrix of segments classified as dead vegetation, soil and buildings. From top to bottom.

2) Initial Population: Ten decision trees were generated at random. Each tree with five branches and two leaves on each that will describe the range of operation of its corresponding node.

3) Fitness function: In total, 10 samples were taken for each element, and the values of the eight indices were calculated for each of these, yielding a total of 13 images per sample. After the trees and indices had been calculated, they were evaluated using the image segments that had been previously selected. As a result a numeric value is given for each tree and this will tell us how suitable is the individual one to solve the problem.

4) Roulette and crossover: The two crossover candidates are chosen randomly using the roulette method, with the most suitable trees receiving a higher percentage of selection. The two individuals proceed to the crossover stage, where a branch is chosen at random for each of the trees, which are then exchanged, resulting in the creation of two new individuals. This process is repeated three times, yielding six new trees for the next generation.

5) Elitism: An elitism of 20% of the population is used, which corresponds to the two best individuals of the present generation becoming part of the next.

6) Mutation: After crossover, a single branch from a random tree is randomly selected and mutated.

D. People Detection

For this section a Support Vector Machine (SVM) are used to train a model to classify if an image contains a person from the top view or not. The Histogram of Oriented Gradients (HOG) are used as the feature representation. Two sets of pictures are used to train the model. One contains a person standing or moving naturally and the other one contains random objects and structures that can be found around.

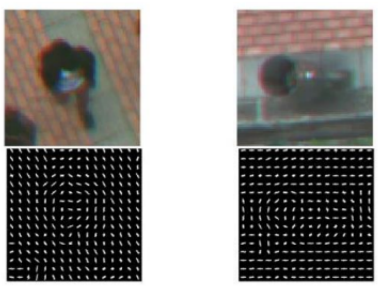

Fig. 2. Sample of the data sets with its corresponding HOG

IV. Online Procedure

In this section the results from the previous Offline section were implemented on ROS(Robot Operating System), as processes can run in different independent nodes that can easily exchange information. Five different nodes were used for the project. The function of every node is described below.

1) Acquires images from the two cameras, rectifies them. Post the processed pictures
2) Uses the rectifies pictures to run the genetic programming algorithm result to detect decaying vegetation. Posts raw RGB images and the processed images.
3) Uses the raw RGB pictures to detect people in the frame using the trained SVM model and posts the composite result.
4) Uses the raw RGB pictures to detect fire in the frame, it posts the composite image result.
5) It takes the result images and displays them.

The five nodes run simultaneously on board the UAV and the resulting images are sent wirelessly.

A. Fire detection

The thermal camera is essential for fire detection. An RGB image and its thermal bands image are required inputs. The thermal picture is threshold for values greater than 0.7 (range: 0.0 - 1.0) and the result can then be composite with the RGB to display a result as in Figure 3. It should be noted that the thermal band can capture the of fire on the ground despite being under the presence of smoke or light clouds.

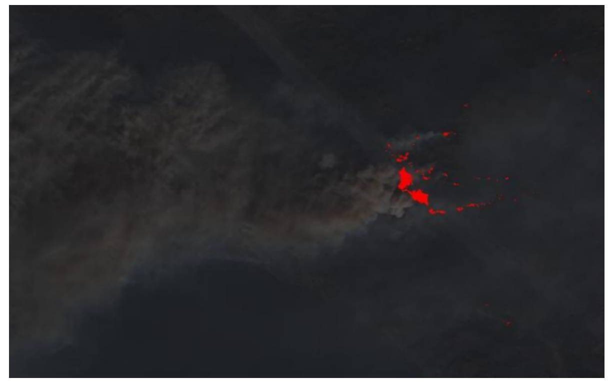

Fig. 3. Fire detection result image

V. Results and discussion

A. Genetic programming result

The proposed script went through 121 generations and producing 17 dominant trees in order to create an individual who has been kept alive for 32 generations and provides a solution to the problem. The result exposed took around 5 hours to be determined and due to the lack of computation power, the built trees in the algorithm were limited on how they grow horizontally and vertically. This is due to the the possibility of a crossover over between branches and leaves. Result can be seen in figure 4.

Fig. 4. Result of the genetic programming algorithm tree

B. People detection result

Despite different tests, HOG in conjunction with SVM does not effectively differentiate that it is a person, for example, mistaking cylindrical waste receptacles for a person. This is due to the way HOG describes the characteristics of the objects in the proposed images, limbs are not fully visible unless there is a displacement of the subject, and in that case creating a noticeable descriptor as shown in the Figure 5.

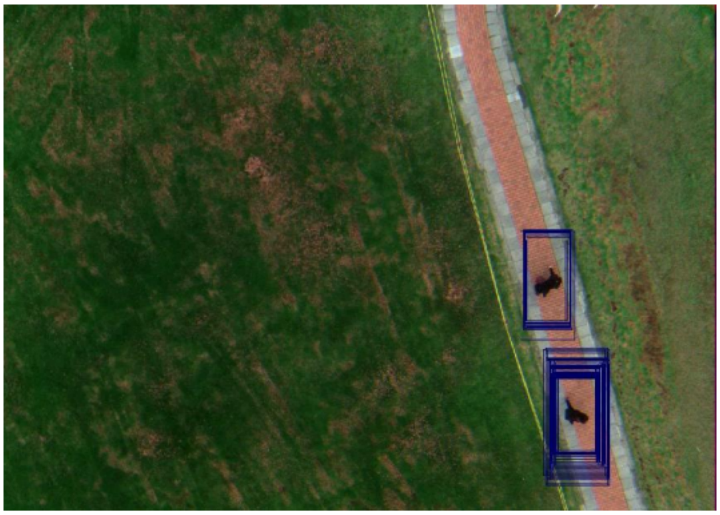

Fig. 5. Result of the people detection algorithm

VI. Conclusion

The presented approach guaranteed an optimal solution for the operation-machine resources relation, as the genetic programming algorithm provided images with a clear differentiation between fire and other objects.

Using HOG and SVM classifiers for people detection represented an issue when recognizing still people and groups of people as they have their limbs close to the body and the classifier requires them to differentiate between each object.

The designed software offered a proper element discrimination as identified dead vegetation, land, people, construction among other objects and highlighted the vegetation. Even though, the resources and equipment limitation represent an improvement area of this project by introducing different data processing equipment that could reduce the processing time and increase the iterations of the genetic program.

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APPENDIX

Annex 1

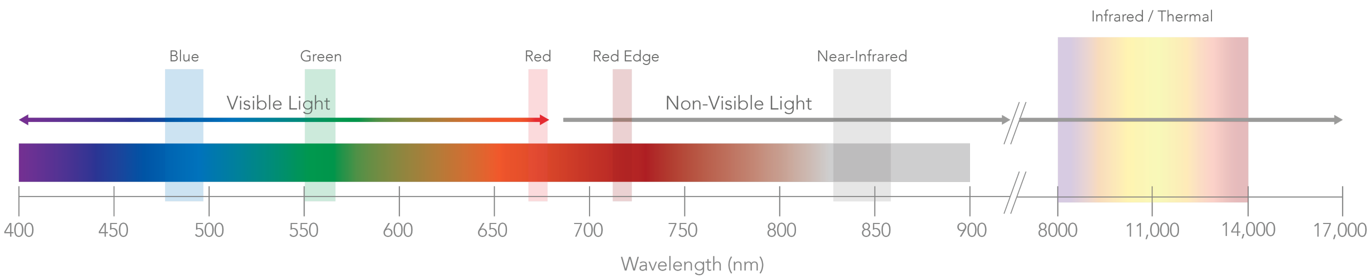

Fig. 6. The Electromagnetic Spectrum and the multi-spectral bands measured