Project of Excellent

Integration of thermal and RGB camera on UAV for cattle and tick-carrier identification

Texas A&M University-Corpus Christi

CONTENTS

Abstract

Unmanned Aerial Vehicle (UAV) has been widely used in Agriculture application thanks to its simplicity, cost-effectiveness, and autonomous flight capability. Ranch management involves identifying cattle and tick-carrier in an area. This project describes the possibility of applying UAV technology in ranch management and monitoring. Cattle and tick-carrier animals identification in many cases relies heavily on human eye observation. This method is usually time consuming and expensive. Applying UAV to this area could reduce the cost of human labor and increase the accuracy of the tracking process. With an RGB camera mounted to the drone, ranch managers can acquire the bird's eye view of the large area that human observation does not offer. Besides, adding a thermal camera to the drone helps managers locate the hiding wild animals and thus increases the accuracy of the cattle tracking. Having the dual camera side-by-side, both thermal and standard RGB images can be obtained at the same time for the same scene. Thermal imaging cameras open the capability of spotting live animals while RGB cameras provide detailed view of the animals. By feeding the live images into an object recognition algorithm, animals in ranch can be classified and detected. This paper presents an application of dual camera set-up on an UAV with object recognition algorithm for cattle and tick-carrier identification. Post processing object classification algorithm, YOLO, is applied to the captured data to determine the animals in the scene. Preliminary results suggest that UAV equipped with dual camera and object recognition algorithm can potentially be used to help farmers identify living objects in farms. The final goal of this research is to create an autonomous vehicle, capable of automatically identifying and providing real-time data of cattle and any other tick carrier animal in one area.

1. Introduction

The uncertainty in food supply due to the population growth and environmental degradation leads to the question of how to raise farm productivity and boost agricultural performance. One of the tool that is recently emerging for efficient agriculture is UAV. Thanks to the development of consumer UAV, farmers nowadays can buy UAVs and use them for agricultural purposes. UAV have been widely used in agricultural activities such as crop surveying, spraying, irrigation management and livestock monitoring [1]- [2] [3] [4].
In animal agriculture, livestock management and is one of the most challenging task. Livestock management and monitoring is the basic of keeping track the number of livestock in once area and keeping they healthy. Livestock health monitor is necessary for farm operation since it provides helpful information of the cattle such as living condition, possible illness or injury and possible threat to the livestock.

The demand for a better cattle health care method comes up recently when Texas cattle fever ticks are once again expanding their range [5]. Cattle fever ticks pose a significant health threat to U.S cattle. Cattle fever attacks and destroys the animals' red blood cells causing anemia, rapid breathing, weight loss, decrease milk production and death [5] The potential host of cattle fever ticks include, but not limited to, cattle, horses, white-tailed deer, and exotic species such as Nilgai antelope and Read deer [6]. As the way to reduce the chance of having fever ticks on the livestock, ranchers and farmers need a tool to effectively locate the location of these fever host animals.

The case study presented in this paper evaluate the possibility of using UAV system for livestock and tick-carrier animals classification. By correctly classify animal, potential host of cattle fever ticks such as Nilgai or Read deer can be detected and thus aid farmer in livestock farming and monitoring.

The UAV equipped with cameras will fly over the ranch autonomously based on a pre-defined path, picture or video will be taken. Then, by analyzing the data through an object recognition algorithm, animals in the ranch will be classified and located.

The important outcome of this system is its ability to classify and localize the animals on the ground. Two cameras, an infrared and a RGB camera, were integrated on the UAV platform as the way to increase chance of detecting and classifying the livestock. With the infrared camera on board, heat signature from the animal can be captured and thus make it easy to spot out a living object. With the RGB camera, visual image of the animal is saved and will be used later for the animal classification and localization process.

Predicting the location of the animals and calling the animal name are called object classification and localization. In this research, we used convolutional neutral network (CNN)-based algorithm called YOLO ("You Only Look Once"). YOLO object detection algorithm to classify animals on the ground. YOLO algorithm is an excellent tool for object classification and localization [7]. Based on deep learning and forward-feedback neural network, YOLO algorithm provides better accuracy and speed that using traditional machine learning algorithm [8].

The remaining parts of the article is structured as follow: The next section introduce related work of livestock health monitoring, UAV and YOLO algorithm. Section 3 describes the experimental methodology in detail. Section 4 describes the implementation and setup. The last section shows the result and conclusion.

2. Background

This section describes the related work of the flowing two areas: (1) Tools used to acquire data, in this case, UAV system ;(2) Object detection and classification using machine vision; the ability to detect and distinguish animal is a major goal of this study.

A.UAV System

UAV has become cheaper and more accessible to researchers thanks to the technological advancement. Among many type of UAV, multirotor UAV is the preferable choice of researchers when conducting a research that requires high accuracy and resolution [9] [10]. Multirotor UAV with aerial filming and photography capability have numerous applications in aerial surveillance [11]. Israel used Multirotor UAV that equipped with a thermal camera for the detection of fawns in the meadows. He detected fawns, deer and other animals when flying the UAV with the camera facing down at 30m [12]. Rudol at el. used multirotor UAV equipped with two cameras to detect human lying or sitting on the ground. The result shows that using two cameras increases the rate of human detection [13]. Radovic at el. applied Convolutional Neural Networks (CNN) on UAV data to automatically detect ground object. Their results show that the CNN recognized the object with 97.5% accuracy.

The proposed system in this paper presents the setup of two sensors on a multirotor UAV. With the aid of YOLO object detection algorithm, the desired objects, livestock and invasive species in this case, will be detected with accuracy.

B. Object detection and classification based on UAV data

Object detection and classification are a common task in machine vision related research. To detect an object in image data, the machine vision algorithm needs to determine the presence of specific feature of an object in the image data. Features of an object could be shape, size, color, etc. After knowing that the features exist in the image data the, the machine vision then compare that feature of the object to a pre-defined feature in a class. If the features of the object in the image data matches with the pre-defined class (object), one can conclude that the object is belong to the pre-defined class.

There are many ways to detect and classify object using machine vision. A simple, less computation power needed way is to use template matching. Parikh at el. applied normalized cross-correlation technique to implement the template matching in detecting birds from images. The results from this approach shows high efficiency for bird detection with low false negative rate.

In recent year, many researchers have shown the interest in using deep convolution neural networks(CNN) for object detection and classification. Convolution Neural Networks is the algorithm that was developed based on how human's brain recognizes and detect an object. Like human, CNN looks at the pictures or an object; learn about the shape, size and detail of it. CNN provides reliable results that traditional machine vision algorithm would not. Sherrah used CNN to label objects in high-resolution remote sensing data. He trained the CNN network with fined tuned remote sensing data in hybrid network context [14]. Qu at el. used deep convolutional neural network(DCNN) based on multi-scale spatial pyramid pooling(SPP) to detect ground vehicles from aerials images. Qu at el. stated that SPP based DCNN adapt better to the smaller size of the input images. The result from this result shows that their approach – SPP based DCNN- improves the detection effect [15]. Wang at el. utilize CNN based algorithm, YOLO, to detect and track birds and nests. Their system provides excellent accuracy and speed [16]. Overall, machine vision related projects are leaning toward utilizing CNN. CNN for object detection and classification not only provides more reliable results but it also can be applied to wide range of application.

3. Method

A. Overview

This project starts with the design of the UAV hardware. After the UAV construction, video and images of cattle were recorded at Texas A&M Agrilife research center. The data analysis of the project includes machine learning, video processing and statistical analysis.

This project has three phases. In the first phase, the UAV was being designed and constructed. In this phase, researcher defined the hardware requirement for the project, construct and test the UAV. The second phase of the project is data acquisition. We flew the UAV over a suspected area; videos and images has been captured for further analysis. There was a total of four flights for this phase. The last phase is to test the working of the image recognition algorithm and come up with a prototype. The UAV Video and images were used for training the algorithm. Once the training is finished, the video from different area will be used as the test sample for the project. The validation of the entire system will also be performed in this phase.

B. UAV Platform Design

We chose to set up a hexacopter drone for this project. Hexacopter offers redundancy and payload that need to carry two side-by-side cameras with a stabilization system. The control of the hexacopter was accomplishes with a 32-bit flight controller board. The main components of the hexacopter includes a frame (Tarot 680), Motors (Emax3510-600kV), electronics speed controller (ESC 30A), RC controller and receiver (Flysky TH9x & Frsky D4R-II), GPS and telemetry (Ublox & 3DR), battery (Tatuu 4S 10000mah), propeller (CF 13 inches) and flight controller (Pixhawk). The payload mounted at the bottom of the frame includes a gimbal control board (AlexMos Basecam 32), gimbal motors, carbon fiber gimbal frame, Gopro Hero 4 and Flir vue Pro UAV.

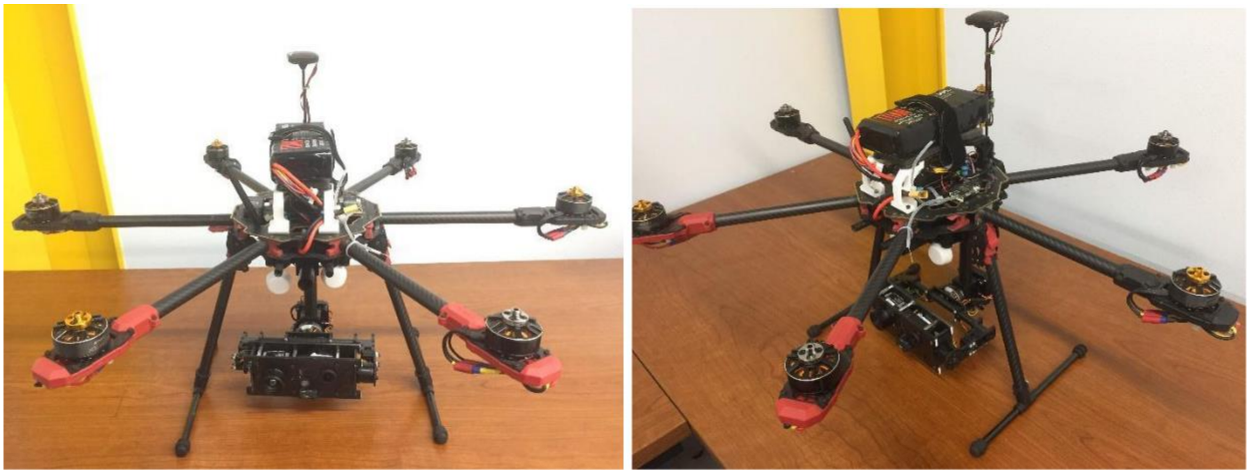

Figure 1. Images of the Hexacopter set up. Six-motors set up for maximum redundancy and payload.

At the time this hexacopter was developed, there was not many options on the market to mount and stabilize the dual camera. Thus, we decided to design our own mounting bracket. After successfully mounted the cameras on the hexacopter, we continued to design our battery holder on top of the drone for the ease of operation and drone's stabilization. The dual camera holder for the gimbal and the battery tray was designed using Autodesk Inventors. Then they got printed out by a 3D print. The material used for this process was acrylonitrile butadiene styrene (ABS).

Flir Vue Pro thermal camera [17] and Go-pro Hero 4 camera [18] are used as the sensors for this research. Flir Vue Pro thermal camera is a light weight, rigid body camera that is made for UAS application. Go-pro Hero 4 camera is a regular wide-angle camera with the capability of recording 4K-resolution video. The UAV also have the capability of streaming live video back to the ground station via radio signal. A dual video screen is equipped at the ground station to demonstrate this feature.

Figure 2. The camera and gimbal. Thermal camera on the left and Gopro camera on the right

C. Image classification algorithm.

The image classification algorithm presented in this paper named "YOLO" project, which stands for "You Only look once". YOLO is an open-source object detection and classification that based on Convolution Neural Network (CNN).

The "YOLO" algorithm has many advantages over other algorithm that implemented Convolution Neural Network software. For example, many traditional CNN algorithms depend on the regional propose methods to draw and determine the potential bounding boxes that contain objects in images. After this step is done, the bounding boxes are scored based on the presence of the objects in the boxes. Then, a sequence of bounding box classification and duplicate elimination is followed. The outcome bounding boxes after classification are re-scored again to ensure the finding and knowing of the object's presence. While these steps are legit and lower the chance of false classification, the process of implementation and computational requirement make it difficult to be used on UAV system. Meanwhile, the "YOLO" algorithm use an unusual way to approach images' classification [refer to figure 3]. "YOLO" first divide image into a sub region . Next, it predicts where the object might be, draw bounding boxes over those suspect regions and compute the probabilities for each region. The bounding boxes with the high probabilities will more likely to contain objects. With this approach, the object is classified and localized based on the whole image, not just the proposed region. Thus, "YOLO" algorithm often yields better result. The other benefits of using "YOLO" algorithm is that it requires less computation power, which means the cost can be cut to minimum while not scarifying the result.

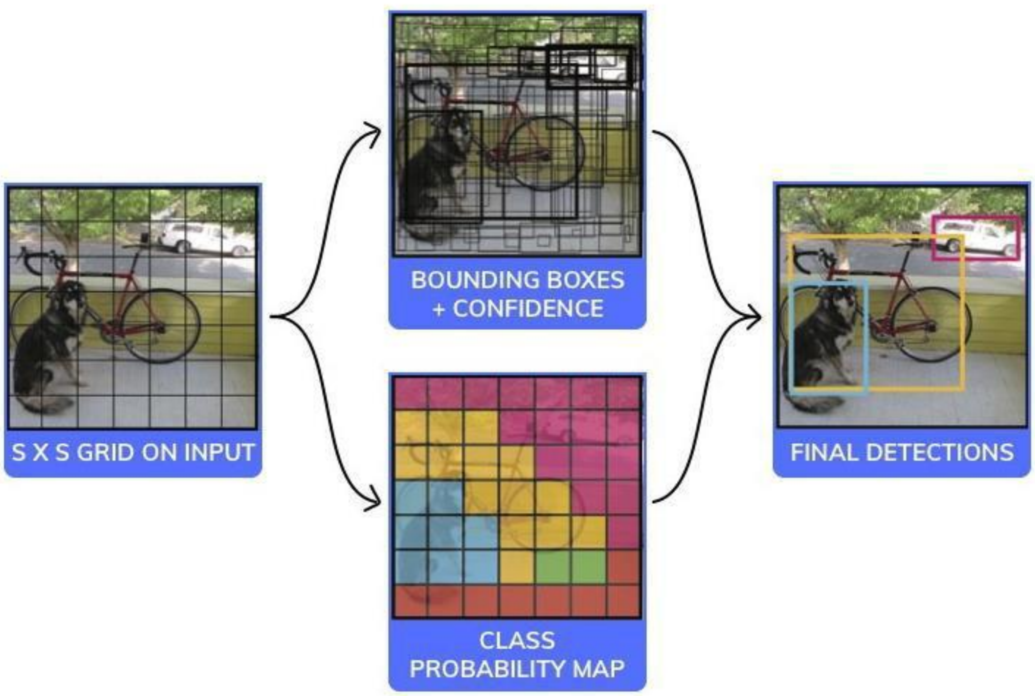

Figure 3: "YOLO" algorithm's process of classification and localization.

D. Build custom model for "YOLO" Algorithm

One objective of the project is to detect and classify cattle and tick-carrier animals from UAV images. To do this, the "YOLO" algorithm need to know how the animals look like in UAV images. Like a human, we learn how to identify an object by looking at it and learning its distinctive features. To get the algorithm learned and familiar with the cattle and tick-carrier animals, we fed aerial images of cattle and tick carrier animals along with animals 'coordinates of each images to it. Figure 4 shows the flowcharts for training and working with this algorithm.

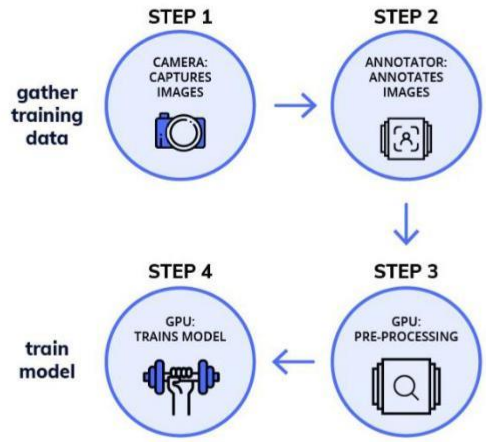

Figure 4: The process of training and using "YOLO" Algorithm

The flowchart of Figure 4 is explained below:

- Step 1- Image Acquisition: The aerial image is acquired by flying the drone over animals.
- Step 2- Image Pre-processing: The acquired images annotated by the operator. The operator looks through each image and draw a bounding box over the animals in the images. The result of this step will be text files that contains coordinates for each animal in each image.
- Step 3 - Pretrain model: Find a pretrain model for transfer learning. This step is necessary to reduce the time and the amount of data needed
- Step 4- Training Model: the images, text files and pretrain model will be used in this step to perform a new model training. The time of the training depends on the physical set up of the hardware. The output of this step will be a new training model.

Using the new training model with the aerial video and YOLO classification algorithm, animal can be classified and localized in real time.

4. Implementation

A. System Hardware

The UAV is connected to a regular computer (ground station) through radio frequency. Operators creates a flight plan in the ground station then upload it to the UAV drone. When it comes to the time for a flying mission, the operator would connect the battery, turn on the cameras, complete all the pre-flight check and take off. Once the drone in the air at a certain altitude, it can use the pre-defined plan as the way to navigate and execute its mission. At this point, the drone is completely autonomous. The operator is there just to monitor and response in case of emergency.

Figure 5: The UAV drone can follow a predefined path that set-up in the ground station

The post-processing includes training the model with aerial images and running the algorithm with the training model. The main computer that is used to train and test the model has a Quad Core I7-7700HQ, with Nvidia GeForce GTX1060 graphics card and a 16GB DDR4 Ram. The computer is installed with Window 10 operating system, along with Open Cv 3.4, Cuda 9.1 and Visual studio 2015.

B. Software and Design

There are three variables of training data that YOLO need to know to successfully classify and localize an object: Object name, bounding box top X and Y coordinate, and box width and height [19]. To get this information for YOLO, we use an open source software name “YOLO_Mark” [20]. “YOLO_Mark” provides an interface for user to draw a bounding box around object in the images. There were total of sixty-three pictures used in this process. Each picture has about sixteen cows, two trucks, four persons and some has three horses. The total training pictures for each class is about one-hundred object.

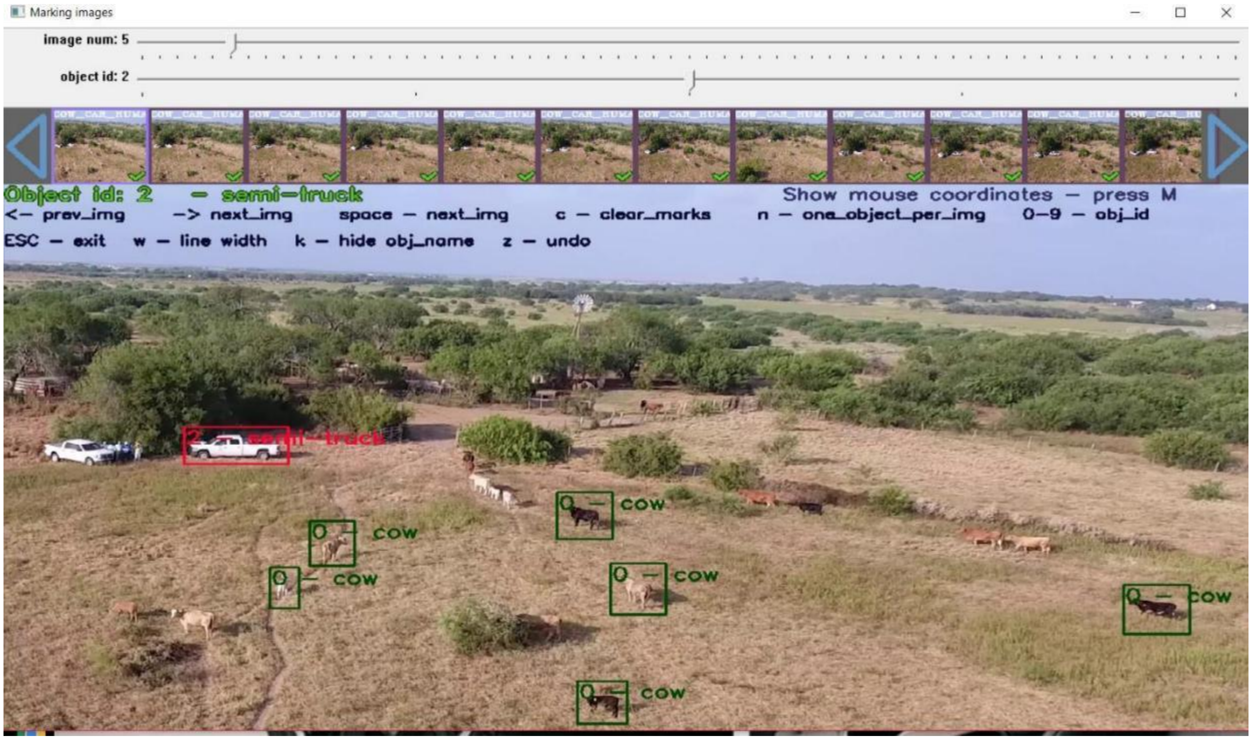

Figure 6: The interface of YOLO_Mark: it allows user to draw bounding boxes and give name to objects in the pictures.

After finishing mark all the objects in the image, YOLO mark will generate a text file with object name, bounding box top X and Y coordinate, box width and box height.

COW_CAR_HUMAN_HORSE_1.txt - Notepad

File Edit Format View Help

```
2 0.393359 0.436806 0.046094 0.056944
2 0.491406 0.423611 0.065625 0.055556
1 0.430469 0.430556 0.006250 0.030556
1 0.426172 0.429167 0.005469 0.033333
1 0.421484 0.425000 0.007031 0.030556
0 0.653516 0.658333 0.028906 0.038889
0 0.537109 0.527778 0.022656 0.050000
0 0.506641 0.559028 0.019531 0.040278
0 0.466016 0.593750 0.021094 0.045833
0 0.692578 0.570833 0.025781 0.050000
0 0.682031 0.507639 0.032812 0.051389
0 0.656641 0.488194 0.014844 0.043056
0 0.639844 0.473611 0.018750 0.030556
0 0.625781 0.459028 0.018750 0.040278
0 0.757031 0.385417 0.015625 0.034722
```

Figure 7: YOLO_MARK output file: The first column is the class; in this case, class 2 means truck, class 1 mean human, and class 0 is cattle. The second and third column are bounding box top X and Y coordinate. The third and fourth column are box width and height.

Once all the images are marked and text files are generated properly, the next step is to download a pre-training model and process with transfer learning. The pre-training model that is chose in this project name “darknet53.conv.74”. The reason for this choice is because of the size and the availability of the pretrain model.

During the process of training the custom model, a graph that display the current average loss is shown. We decide to stop the training when the current average loss number was 0.6835, which was no longer decrease. The current average loss signifies the error of the process where the training model is tested on the current training images. This process is like how a student study for a test and do a test. In this case, a student study for a test is like the algorithm learn features about cattle images. The average loss of the verification process in training algorithm is like the test grade that reflect student’ study process.

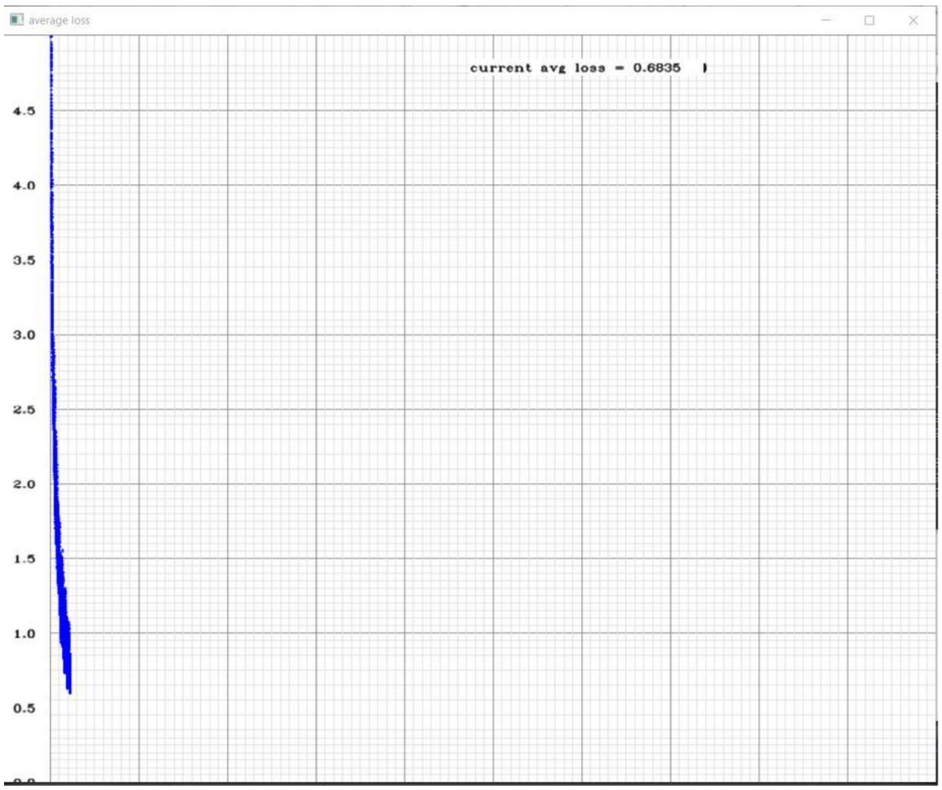

Figure 8: The graph showing the current average loss. The lower the loss, the higher the classification and localize rate.

With the current hardware, we decided to stop the training when the current average loss was about 0.5. It took the computer about 35 hours to reach to this average loss number. The iteration weights number was 11300 at the time the current average loss gets to 0.5. The iteration number can be understanding as the repetition of computational procedure applied to the result of a previous application. “YOLO” algorithm constantly applies computational procedure to the last iterations to obtain successively closer approximations to the solution. In average, it took the computer sixteen minutes to complete one-hundred iteration on this system hardware. In other words, the machine looks through images, notes down all the feature of the objects in the images in six-teen minutes. When it come to the next iteration, the machine will use the notes for the previous iteration, learn from it, and extract new feature from the same training data set.

The training time depends mostly on the physical set up of the hardware. To verify this theory, we trained the model on a different computer with different hardware set-up. Indeed, the new computer has better hardware. It has the Core I7-8700K CPU, 32 GB of RAM and NVIDIA GTX 1080 24 GB graphics cards. With this set up, it took the system about 28 hours to reach to the current average loss of about 0.5. With this et up, it took the computer in average of eight minutes to complete one-hundred iteration. The training on the second PC greatly reduce the total training time by half.

5. Results

A.The performance of the thermal and RGB camera on the drone

The results from the RGB and thermal cameras suggest that this combination have a lot of potential in detecting animals (thermal camera) and classify the animal (RGB camera). Figure 9 shows the data capture from the drone. The data was taken on a mid-winter day with the temperature of 65-degree Fahrenheit. The cattle, which are shown in white pixel, stand out from the surrounding area and background. When flying the drone on that day, we noticed that it was much easier to spot the cattle on the thermal images than on the RGB images. This means that the thermal images can also help the drone pilots with navigation and finding living cattle. The thermal images contain less details and amplify on the contrast of the object with the background, which made it easier to spot the object from the image. On the other, the RGB images provide many details that are small and can be distracting.

Figure 9: The RGB and Thermal images from the drone. The cattle are easier to detect in thermal images.

The thermal detection range was surprisingly far with the thermal camera. Figure 10 shows the benefit in range of detection of the thermal camera over the RGB camera. While it is hard to know if an object is a living thing or not, it is very easy to do so in the thermal camera image. This result re-ensures the benefits of having dual cameras for cattle management. With the RGB camera, object can be seen and classification; with the thermal camera, object can be detected,

Figure 10. Thermal camera can detect objects from far away; provide helpful information for pilots during flight.

The disadvantages of the thermal camera in general and the thermal camera in this project are price and resolution. Thermal camera usually is three to four time higher than the regular RGB camera. However, the resolution of them are usually not high. For example, the thermal camera in this project cost around $3000 with the resolution of 640x512 pixel. While the regular RGB is on around $400 with the resolution of 3840 x2160 pixels, about 5 time higher than the thermal camera.

B.The Accuracy of The Trained Algorithm

The detection and classification results are greatly different when using the train model and default (untrained model). There are two default models used in this project : YOLOv3 and Yolo9000. These are the different training file that usually be used for general purpose. For example, the Yolo9000 contains 9000 different objects, which mean it has the capable of calling 9000 different object names.

Without the customized training model, using YOLOv3.weights, YOLO Algorithm still can detect and localize objects. However, it can't classify the objects to the level of accuracy where the information can be used for detecting cattle and tick-carrier. In the case of using Yolo9000.weights, the algorithm can detect more object, but the accuracy is low. On the other hand, with the training model that is customized for objects in the ranch, YOLO Algorithm can now detect and classify objects with high accuracy. The different here is that, our YOLO custom training file are train with less objects than YOLOV3 and Yolo9000. Therefore, the yolo custom training file can be specialized in the objects and get less interrupts from other objects when performing the classification

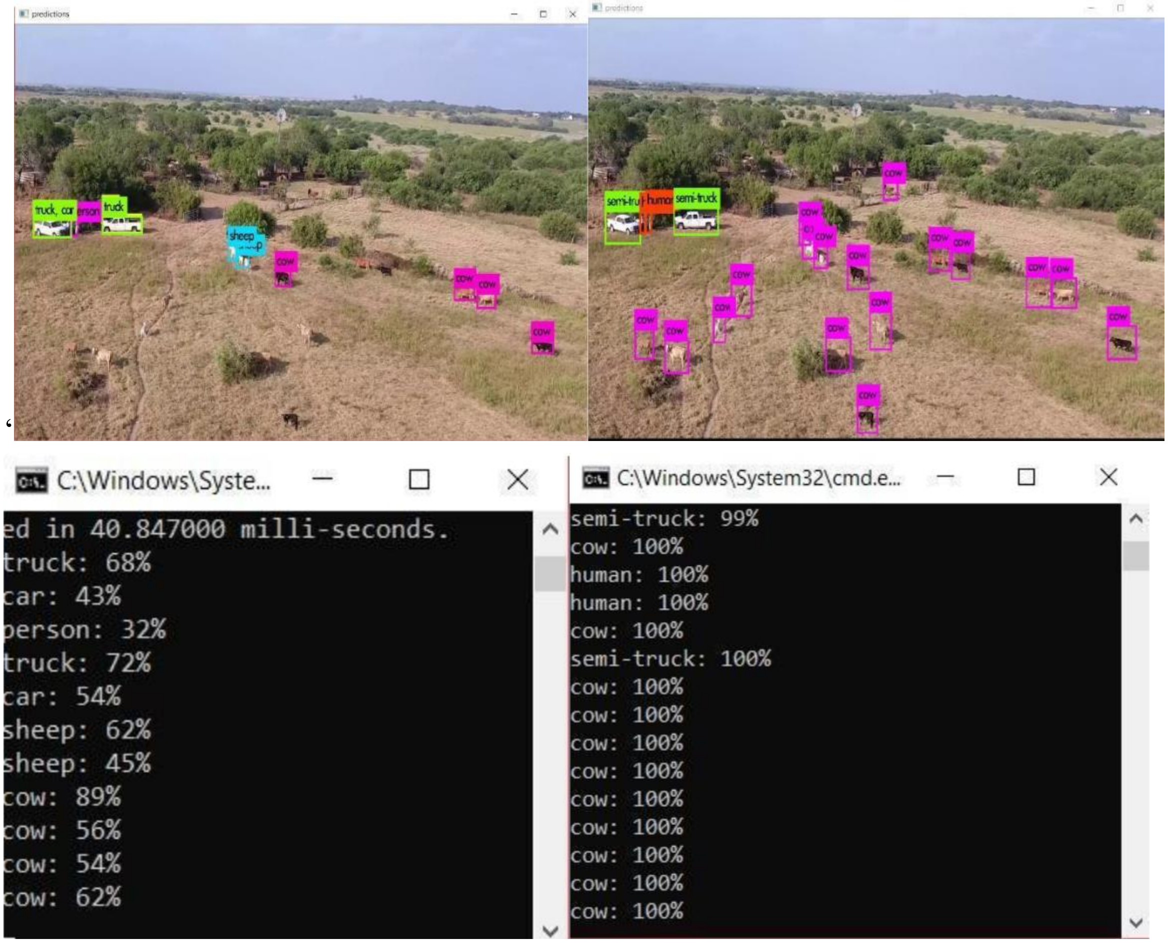

Figure 9. The result generates with "YOLO" algorithm before (left-Yolov3) and after(right). Top left figure: YOLOv3 could not detect all the objects in the scene, some classification is not correct. Bottom left figure: The confidence level of detected object for YOLOV3.Top Right figure: The result from our custom training data. Bottom right figure: The confidence level of detecting the right object for our custom training data.

Figure 10 shows the performance of our training model's performance when working with unfamiliar data. In this case, an image of the scene that different than the training's scene is used to check the performance of the algorithm. Our training data could classify the object well with the average accuracy of 73% certainty, while the localization and detection can be better. To increase this number, most likely the certain ways is to increase the training data (increase the number of learning picture) for the training process.

Figure 10. Our custom data's performance with unfamiliar data. The classification is good with the average of 73% certainty level.

Figure 11 shows the performance of Yolo9000 on the same scene used in Figure 10. The result shows that Yolo9000 detect and localize object well but the classification. Out of all cows in the images, Yolo9000 was only able to classify correctly one cow with 53% certainty level.

Figure 11. YOLO9000's performance on the unfamiliar data. Only one cows was classified correctly.

The experimental result revealed that the classification's accuracy decreases with increasing objects in the training data set. It also suggests that training is necessary to classify object with higher accuracy.

6. Conclusion

Dual camera drone with classification algorithm have been developed to aid farmer in localizing and classifying objects in the farms. The dual thermal and RGB camera with live streaming video has demonstrated the capability of helping farmers detect and classify cattle or tick-carrier in the farm. The real-time classification algorithm is optimized by giving it the training data of the real object that most likely be in the farms. The cattle have been detected and classified at varying real-time input conditions, and the algorithm was able to visualize the cattle by drawing bounding boxes across the frame. The experimental results suggest that training the algorithm is necessary to classify and localize objects with elevated level of confidence and accuracy. Moreover, the better the hardware, the faster the machine can be trained. The limiting factor that might affect the detection and classification process is camera resolution and the size of the training data. More training data is expected to significantly increase the performance of the algorithm. Future work involves developing an end-to end system to help farmers operate the system easier.

Acknowledgment

The authors thank Dr. Jinha Jung and GARS LAB for instruction, helping, providing resources and funding this project.

References

[1] Anjin Chang, Jinha Jung, Murilo M Maeda, Juan Landivar, "Crop height monitoring with digital imagery from Unmanned Aerial System (UAS)," *Computers and Electronics in Agriculture,* vol. 141, pp. 232-237, 2017.

[2] Zhou Qingqing, Xue Xinyu, Qin Weicai,Cai Chen, Zhou Liangfu, "Optimization and test for structural parameters of UAV spraying rotary cup atomizer," *International Journal of Agricultural and Biological Engineering; ,* vol. 10, no. 3, pp. 78-86, 2017.

[3] Perea-Moreno, Alberto-Jesús; Aguilera-Ureña, María-Jesús; Larriva, Jose-Emilio Meroño-De; Manzano-Agugliaro, Francisco, "Assessment of the Potential of UAV Video Image Analysis for Planning Irrigation Needs of Golf Courses," *Water; Basel,* vol. 8, no. 12, p. 584, 2016.

[4] Pablo Chamoso, William Raveane, Victor Parra, and Angélica González, "UAVs Applied to the Counting and Monitoring," *Advances in Intelligent Systems and Computing,* pp. 71-80, 2014.

[5] R. Williams, "Texas cattle fever ticks are back with a vengeance," Texas A&M AgriLife Communications, 2 Febuary 2017. [Online]. Available: https://entomology.tamu.edu/2017/02/02/texas-cattle-fever-ticks-are-back-with-a-vengeance/. [Accessed 20 May 2018].

[6] S. Swiger, "Texas Cattle fever Ticks," Texas A&M Agrilife Extension, 2017.

[7] Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016.

[8] Peiming Ren, Wei Fang, Soufiene Djahel, "A novel YOLO-Based real-time people counting approach," in *Smart Cities Conference (ISC2)*, Wuxi, China, 2017.

[9] Albert Rango, Andrea Laliberte, Caiti Steele, Jeffrey E. Herrick, Brandon Bestelmeyer, Thomas Schmugge, "Research Article: Using Unmanned Aerial Vehicles for Rangelands: Current Applications and Future Potentials," *Enviromental Practice,* vol. 8, no. 3, pp. 159-168, 2006.

[10] C. A. Rokhmana, "The Potential of UAV-based Remote Sensing for Supporting Precision Agriculture in Indonesia," *Procedia Environmental Sciences,* vol. 24, pp. 245-253, 2015.

[11] R.W. Beard ; T.W. McLain ; D.B. Nelson ; D. Kingston ; D. Johanson, "Decentralized Cooperative Aerial Surveillance Using Fixed-Wing Miniature UAVs," *Proceedings of the IEEE* , vol. 94, no. 7, pp. 1306-1324, 2006.

[12] M. Israel, "A UAV-BASED ROE DEER FAWN DETECTION SYSTEM," *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* pp. 1-5, 2011.

[13] Piotr Rudol ; Patrick Doherty, "Human Body Detection and Geolocalization for UAV Search and Rescue Missions Using Color and Thermal Imagery," in *Aerospace Conference, 2008 IEEE*, Big Sky, MT, USA, 2008.

[14] J. Sherrah, "Fully Convolutional Networks for Dense Semantic Labelling of," Defence Science & Technology Group, Australia, 2016.

[15] Tao Qu, Quanyuan Zhang, Shilei Sun, "Vehicle detection from high-resolution aerial images using spatial pyramid pooling-based deep convolutional neural networks," *Multimedia Tools and Applications,* vol. 76, no. 20, pp. 21651-21663, 2017.

[16] Qiaosong Wang, Christopher Rasmussen, Chunbo Song, "Fast, Deep Detection and Tracking of Birds and Nests," in *International Symposium on Visual Computing*, Las Vegas, 2016.

[17] Flir, "FLIR Vue Pro," Flir Systems, Inc, 2018. [Online]. Available: https://www.flir.com/products/vue-pro/. [Accessed 28 November 2018].

[18] GoPro, "Gopro.com," GoPro Inc, 2016. [Online]. Available: https://gopro.com/content/dam/help/hero4-silver/manuals/UM_H4Silver_ENG_REVA_WEB.pdf. [Accessed 29 November 2018].

[19] AlexeyAB, "Yolo-v3 and Yolo-v2 for Windows and Linux," 2018. [Online]. Available: https://github.com/AlexeyAB/darknet. [Accessed 19 May 2018].

[20] AlexeyAB, "Github.com," GitHub,INC, 2016. [Online]. Available: https://github.com/AlexeyAB/Yolo_mark. [Accessed 29 November 2018].

[21] Mansu Parkh, Miral Patel, Dulari Bhatt, " Animal Detection Using Template Matching Algorithm," *International Journal of Research in Modern* , vol. 1, no. 3, pp. 26-32, 2013.