Efficiency of Infrared Imaging in Self-Driving Cars

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Abstract

The purpose of my research was to determine the efficacy of thermal imaging to assist self-driving vehicles avoid obstacles. I hypothesized that infrared imaging would be more effective at detecting warm blooded animals than traditional imaging solutions such as color sensors. My research aimed to solve one of the major problems limiting self-driving vehicles' widespread adoption, the high cost of AI accelerators capable of quickly running the object detection software and the long development cycle. To test the viability of infrared imaging two models, a color sensor and a thermal sensor were used to obtain images of the target. The target in this case was a deer model six inches tall. Using image recognition software Yolov 7 the models were tested to find the time in which they achieved a 99% detection rate. The time is measured in the number of epochs until the threshold has been met. The threshold in my experiment was a false detection rate of 0.05%. Which means out of 10,000 images, it would categorize 5 images incorrectly. After the software analyzed the results of the two models it was found that the thermal model met the threshold within 200 epochs while the color model met the threshold within 250 epochs. Given a constant epoch time of 28.8 seconds this is a time savings of 24 minutes or 20%. This led to the conclusion that the use of an infrared model can reduce the training time of a self-driving vehicle's object detection by 20%.

Introduction

Self-driving cars were once a thing of fiction only seen in sci-fi movies, but now with the release of Tesla FSD or Full Self Driving beta, we can get a glimpse of the world once only seen in fiction. Self-driving vehicles are a new idea with the release of purchasable cars such as Teslas that brings the concept of a vehicle capable of self-driving closer to widespread use than was thought possible. This is a complex topic broken down into many sub-sections. A self-driving vehicle consists of sensors responsible for detecting obstacles and predicting the path of objects in motion. Then this data is processed by a machine learning algorithm that identifies objects, indicates the movement of objects, and controls the throttle, brake and steering of the vehicle to get from point A to point B safely. But many factors limit self-driving vehicles from being proper autonomous vehicles because current models used by Tesla still require the driver to keep their hands on the wheel and be observant if the car needs human assistance. According to NPR, there have been 400 crashes related to semi-autonomous vehicles, and 273 were caused by Teslas (The Associated Press). The use of self-driving vehicles in their current state is dangerous to both the vehicle's driver and others around the vehicle. Thus, advancements must be made before true self-driving vehicles can be implemented on roads.

Current problems facing self-driving cars are caused by the unpredictability of humans and other living beings. Machines need to be better at predicting these movements. Humans can make decisions that a machine-learning algorithm was not programmed to consider. This can lead to the vehicle not predicting the car's or organism's movement correctly, leading to a crash. This research focuses on improving the detection systems in autonomous vehicles. This is because the detection systems of self-driving cars are one of the main factors bringing the cost of self-driving vehicles up. For example, the price of Tesla's entry-level tesla model 3, which starts at $43,000, adding the complete self-driving package to the vehicle increases the price of the car by $15,000 (Tesla). The high cost of the sensors limits the availability and use of self-driving vehicles on the road. The problems facing self-driving vehicles are numerous and complex. But how do self-driving vehicles function and why are they so hard to make and improve upon?

Self-driving vehicles have various systems that are used to achieve motion. Sebastian Thurn of Carnegie Mellon University produced a car made for the DARPA Grand Challenge. It was made up of five laser interfaces and a radar interface, and the information from the interfaces is sent to a machine learning algorithm (Thrun). The robot that Carnegie Mellon used for the Darpa Grand Challenge was a more basic version of the self-driving vehicles seen today. This is because the study was done in 2006 when self-driving cars had yet to reach the consumer market. In the autonomous vehicle used by Carnegie Mellon, the cars did not have to avoid other moving vehicles allowing for a simplified array of sensors. In modern self-driving cars, cameras are used to identify objects using an object detection model. The job of the object detection model is to tag objects with an identifier so that the vehicle can use sensors such as radar or lidar to identify the object's distance and then the possible movement of the object. Constantine Papageorgiou at MIT, created an image detection system that effectively identified humans using black and white, and color images. Still, balancing correct detections and detections where the object is not present is required because a 100% detection rate is not possible without intermittent failures. (Papageorgiou and Poggio). Constantine at MIT found that with an object detection model, as the detection rate approaches 100%, the false positive rate also proportionally increases. In Papageorgiou’s research, he was able to achieve a detection rate of 80% without the introduction of false positives. As seen in Constantine’s work, a color image has a 6% higher detection rate than a black and white image. This was due to the color image containing more data than the black and white image. Hence, the introduction of more data to the object detection software brings the detection rate of the model up proportionally to the amount of new data given to the software. Thus, the introduction of more data will bring the detection rate of objects up and the training time down; therefore, this research aims to find a new sensor to obtain more data to feed to the image detection model. Now let's get into the machine learning part of self-driving vehicles.

Autonomous cars use lidar, radar, and cameras to identify their surroundings. The sensors can be put into two different categories: the range-finding sensors and the object detection sensors. The camera is used to determine the object, and then either lidar or radar can be used to identify the distance to the object and the size of the object. According to Shunqiao Sun, the requirement for a sensor for self-driving vehicles is that the sensor has to be low cost, have a small size, and have a high resolution (Sun, 99). Combining these aspects makes a sensor a viable option for self-driving vehicles. The current sensors in self-driving cars such as Tesla have all such features but are prone to not work in the case of poor weather conditions. As mentioned on Tesla's website, self-driving features are unavailable in situations such as rain, snow, fog, or other low visibility conditions (Tesla). This has led to the present issue with self-driving cars due to the sensors used to detect their surroundings. They are prone to perform poorly in conditions of low visibility. This is caused by using a camera for object detection, so in the event of poor visibility, The car disables self-driving capabilities.

Self-driving vehicles are prone to crashes due to low visibility and the unpredictability of living organisms. Current self-driving models do not allow the driver to take their attention off the road because they are prone to make mistakes and request the driver's assistance. Without a way of sensing their surroundings in low visibility environments, self-driving vehicles do not operate in a vacuum weather conditions can change and negatively affect visibility. Introducing a new sensor to autonomous vehicles can aid in the detection of objects in non-ideal environments. Thus this research aims to introduce a new sensor to autonomous vehicles to improve visibility in low-visibility situations. The sensor used was a FLIR infrared sensor. How can the use of infrared imaging aid in the detection of living organisms?

Method

In this research, the yolov7 software was used for object detection. Additionally, the target that was used to test the object detection sensor was a 4” model of a deer heated using a 17.3-watt Peltier unit. The Peltier unit has a heatsink attached to one side to ensure that a temperature of 40 degrees Celsius can be achieved. Then a metal block was used to test the sensor’s reaction to an object it was not trained on. The results were placed into folders labeled if they are the thermal image, the color image, and what the image was. When finished the system will output a text file that will say the number of detections, the number of false detections, and the number of no detections in the image set.

The first part of the method is the infrared camera which will show the model's temperature. This was used to identify the detection rate of the infrared camera compared to the detection rate of a color image. For the infrared images, a FLIR one sensor was used to obtain the images. The FLIR One has an accuracy of +-5 degrees Celsius. In my testing, I have found that the accuracy is lower at further distances, so the FLIR camera is placed six inches from the model so that the accuracy is as high as possible. The FLIR camera is attached to an iPad that records video and splits it into individual frames. An image was taken every second for 500 seconds to obtain 500 images. This was repeated using the infrared sensor and the color image sensor.

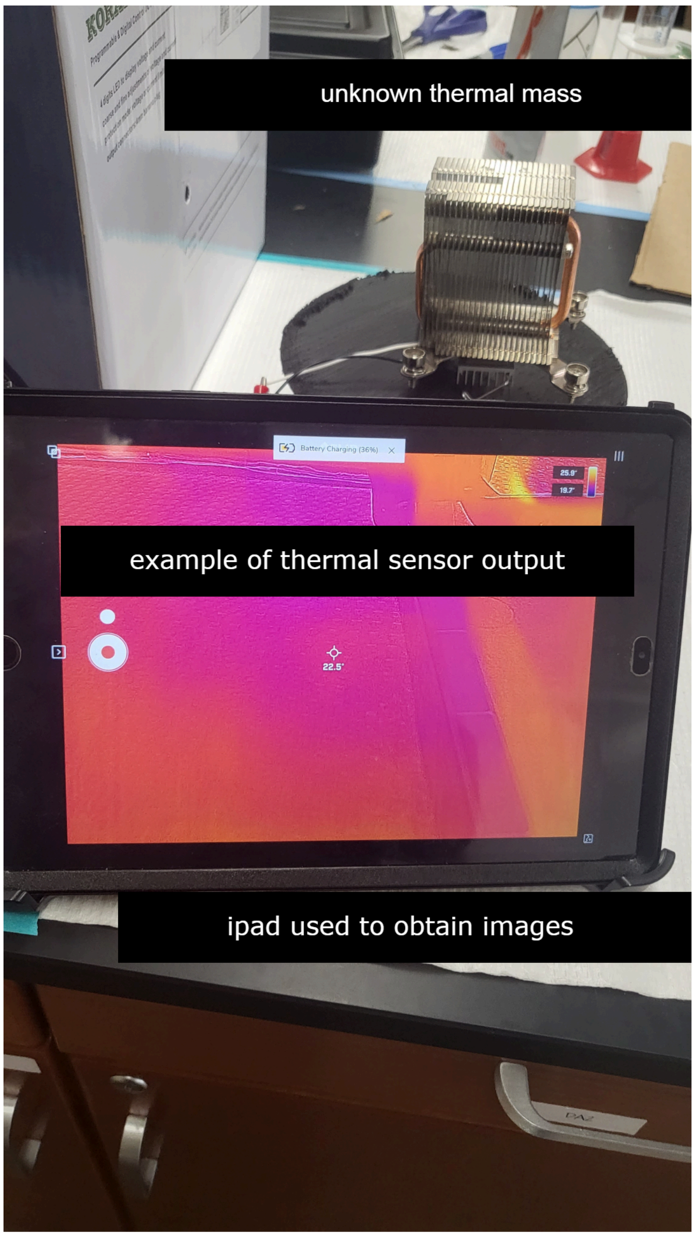


Figure 1

Figure 1 shows the setup which includes an iPad to obtain both thermal images using the FLIR thermal sensor and color images. The unknown heat source was a heatsink due to the high dissipation of heat used for calibration. In orange and blue the thermal sensor output is shown. The thermal heat heatsink is replaced with the target (deer model) for the collection of data.

The Peltier unit was chosen to heat the model deer, the target was made of PLA. which has a low melting point, so other forms of heating, like a hair dryer, will cause the model to deform and fall apart. The Peltier unit avoids this because the temperature output can be changed by changing the input voltage. In this research, the voltage used was 1.25 volts because it allowed the Peltier unit to reach a temperature of 40 Celsius. For the initial heat-up of the model, the voltage was set to 2.5 volts to heat the model to the desired temperature. Then the voltage is dropped to 1.25 volts and allowed to cool to reach 40 Celsius.

Figure 2

Figure 2 shows the output of the thermal sensor, in the image the orange color signifies a hot surface and blue signifies a cold surface. In the image a Peltier unit was applied to the heat pads prior to the image being taken. The box around the target signifies a correct detection of the target.

A box was set up with different amounts of light and images were obtained. Pictures were taken at 0%, 25%, 50%, 75%, and 100% light. This will simulate different light levels at other times of the day. The light must not be in the frame of the camera because on the color image, this will cause a lens flare making the image unusable. For both the color and infrared, the light source for both the color and infrared sensors was placed out of the view of both sensors because if the light was in the view of the thermal sensor it would show up as a heat source and cause problems in the training process. Additionally, for the color sensor, if the light was in the view of the sensor the sensor would have a hard time focusing on the model.

The yolov7 model was chosen given that the model is open source allowing the implementation to output my data into a text file for easy analysis. The yolov7 model is the 7th generation of the Yolov model. It has many implementations on GitHub that were used as references to build the model that I am using. The model required images to train the object detection model for these 13-minute videos to be used for the model's training. The videos were then broken down into individual images, 60 images per second and 46,800 images per video. As seen in the documentation for the yolov7 model, a training set of over 10,000 is recommended for good results, Therefore, it was chosen to take videos of the models and spin them to obtain the images used.

After the image detection model was trained, groups of 500 images were input to the yolov7 software, and the results were outputted as a text file with the average and the data points.

After the data was collected, the results were compared to the effects of a trainable system for object detection to ensure that the collected values are not abnormal. An abnormal result would be one that is less than or greater than the target MAP value by 5%. The target MAP value was determined to be 99.5% as it was a good goal for an object detection model. If the results are abnormal, the data was recollected with alterations to the object detection model to remove the anomaly. To remove the anomaly the images would be recollected and the images would be marked with the target. A MAP of 100% should not be obtained because this means the false positive rate will be high. A result of 80% to 90% is a result that indicates that the infrared sensor is viable for autonomous vehicles. Any results lower than a 80% MAP value indicate that the infrared camera is not a viable sensor for object detection in autonomous vehicles. I hypothesize that the infrared model will obtain a result of 5% improvement over the color model because this was the improvement found between black and white and color images by Tomas Pagio.

To ensure that the values are reproducible, the model will be run ten more times after the data is proven not to be anomalous. The average of the ten runs will be taken to ensure that the data collected is reproducible and accurate.

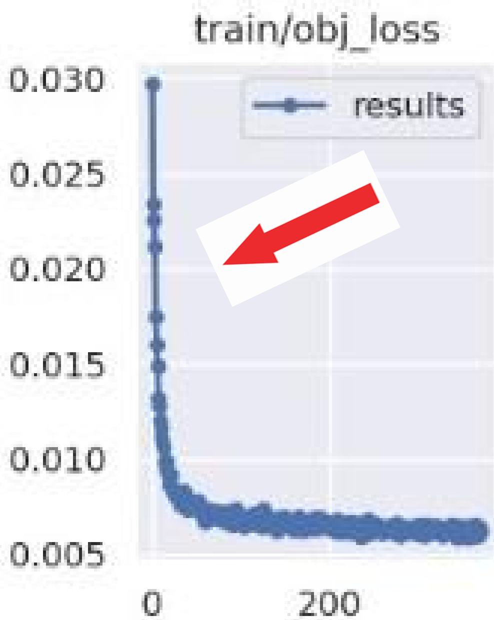
Results

As a result of the development and testing of the image detection software it was found that the infrared and color sensor had very similar end conditions. Both implementations of the software had a MAP value of 99.5% which means that in 100 images it will detect 99.5% of the images that are tested. The infrared sensor detected 100 of 100 images showing a 100% detection rate while the color sensor achieved a test result of 99 of 100 images detected. A larger text size would be required for the MAP value of 99.5% to be shown in the software due to the results of the test being a whole number. The MAP value shows that over the final tests on the implementations of the software they both achieved a detection rate of 99.5% averaged over the last two tests.

The differences in the software implementations can not be seen in the test results because both implementations had no trouble achieving the detection rate of 99.5% over the test images. The differences of the 2 software implementations were seen in the training loss graphs which track the amount of change in the detection software. A lower value on the y axis signified that the software is approaching the end of the training process. The training ends once the MAP value reaches 99.5% or the software implementation is more than 1000 trials. Thus, a steeper curve indicated that the software implementation would be able to train in a shorter amount of time relative to the control software implementation.

The two graphs below (Figure 3 A and B) show that the two implementations of the software with the thermal on the left and the color on the right are both able to achieve a result that is at the desired value of 99.5% detection. The thermal table shown on the left has a quick regression of the change in results which settles to a result change of 0.007 or 0.7% change per trial. The thermal image started with a result difference of 3% showing that the software implementation was getting 3% more efficient per trial. In contrast to this the color image data in table 2 shows that the color sensor has a slower start with a difference between trials of 2.5% showing that the thermal software implementation has a .5% advantage over the color software implementation causing the thermal implementation to train at a faster rate and not require the 300 trial minimum used while the color software implementation would need all 300-trials to obtain the same end result.

Figure 3



A

B

Figure A shows the thermal sensor. The false positive rate slowly reaches the threshold of 0.005% false positive rate.

Figure B shows the color sensors results. The color sensor reaches the threshold of 0.005% false positive rate slower than the thermal sensor does.

Discussion

As seen in the results of the data collected, both sensors are capable of a MAP value of 99.5%. The differences in the 2 sensors arise when you look at the training object loss graphs which show the number of trials that would be required to train the software on a given sensor to the desired accuracy. Graph A and B show that the thermal sensor is able to train at a faster rate and the minimum number of trials could be reduced to speed up the training time of the software. In contrast the color sensor needed almost all 300 minimum trials to achieve a MAP value of 99.5%. The thermal sensor would be able to train within 50 less trials leading to a shortened training time. The thermal sensor and the color sensor took 2 hours to train meaning that ending the training 50 trials short would lead to a 20-minute time saving or a reduction in training time of 16%. In a scaled-up implementation of the software a 16% training time reduction could mean reducing the prices associated with operating a computer capable of training the software, which can cost upwards of $100,000 per server. A reduction in training time would lead to the tools required for the testing and production of image detection software to come down as a result of the decreased time required ruining the high-cost servers.

Additionally, the infrared sensor has an advantage of the sensor already being mass produced and used in other sectors. The company that was found to be the best to acquire infrared sensors for autonomous vehicles would be FLIR. FLIR was chosen because they have been producing infrared sensors since 1978 in all sectors ranging from contractor use to the military. The FLIR ADK sensor line would be a good selection for autonomous vehicles because the sensors come in a range of resolutions and field of views allowing companies to use the best fit sensor for their autonomous vehicle.

Limitations

The infrared sensor would not be viable for many different uses due to the higher cost per performance of the infrared camera and the extra effort that would be needed by companies to incorporate the infrared sensor into their autonomous vehicle. The infrared sensor would not be viable for road cars because on most roads in populated areas the roads are lit which would allow the color sensor to perform at the same level as the infrared sensor. The infrared sensor would not be viable in such use cases because the infrared sensor has a higher cost than a color sensor. This does not mean that the infrared sensor does not have its benefits. The infrared sensor is still a cheaper alternative to sensors such as lidar and radar. But in ideal use cases the color sensor is a cheaper and already implemented sensor. This is not to say that the infrared sensor has no uses, just not in the consumer sector.

The infrared sensor has advantages over the color sensor such as low light performance and better performance in bad weather conditions. These are advantages that are achievable with other sensors such as radar and lidar. Although radar and lidar also have disadvantages mainly the high cost associated with radar and lidar solutions for self-driving vehicles. Additionally the thermal sensor is a smaller sensor which allows it to be easily placed into an autonomous vehicle. Solutions such as radar and lidar have issues with the size and the weight of the sensors which make the sensors harder to implement into self-driving vehicles. Lastly the infrared sensor has a much lower power draw relative to the radar and lidar solutions due to its smaller surface area to cool for optimal performance.

Real World Benefits

The infrared sensor would be applicable in many different sectors for the automation or improvement of autonomous vehicles. The first use case is in the farming sector due to the remoteness of farms and their use of dangerous machinery to animals that might be hit by the machinery. Automation is already in the farming sector and this is why it is a good sector for the deployment of infrared based object detection for autonomous operation of equipment.

The second sector that would see benefits from the infrared sensor is the off-road vehicle market. Off-road vehicles would not be able to use autonomous driving at this time due to limitations in technology in computing and GPS, but infrared sensors would be a good first step to autonomous off-road vehicles. The main reason that off-road autonomous vehicles are not widely used is the cost of the AI computer models necessary to operate such a vehicle and also adequate detection of the vehicles surroundings. Infrared imaging offers a solution to better detection of a vehicles' surroundings bringing offroad autonomous vehicles one step closer to widespread adoption.

Lastly the infrared sensor could be used in the drone sector to assist in the avoidance of collisions with humans or other animals. The drone sector at the current time has options for autonomous drones but none for low flying drones used in highly populated areas for uses such as security or tracking of livestock for farmers. The infrared sensor could allow the low flying drones to operate autonomously without the risk of collision into people or animals. Additionally, drones are low on space and cannot carry a lot of weight so the sensor must be light and small to fit on many different sizes and shapes of drones. It is for these reasons that infrared imaging would be a good fit for uses in drones for tracking of both humans and of animals.

Infrared imaging is not a solution to all of the problems facing autonomous vehicles but it offers a step in the right direction for the industry.

Conclusion

The use of the infrared sensor in autonomous vehicles would not be viable for all cases. Where it is applicable, the thermal sensor would be viable for the detection of living organisms. My image detection model was only received data for one animal so training a model on a wide variety of animals would be a good test of the versatility of infrared beyond my findings. Other sensors would need to be used on the autonomous vehicles though a thermal sensor could replace an expensive sensor such as radar sensor. With the lower price of the infrared sensor the automation of fields such as farming and others described previously would be less expensive leading to a faster conversion to autonomous vehicles.

Thermal imaging, if implemented correctly could be the solution to many of the problems facing autonomous vehicles such as the high price of sensors and hardware to run the object detection. Thermal imaging has the potential to solve both of those problems. As seen in my research the thermal model is able to train in less time and run at a faster rate. This could lead to the price of these cars decreasing as the AI compute modules on autonomous vehicles are one of the most expensive components. More efficient object detection is one of the solutions to bring the price of autonomous vehicles down.

Although price is not the only benefit to infrared imaging, another is the visibility of infrared imaging. Traditional sensors on autonomous cars need a well lit environment to operate but thermal imaging does not. Thus making thermal imaging a good replacement or addition to existing autonomous vehicles.

Though my paper does not give a solution to other problems that are facing autonomous vehicles such as the large amount of energy required to power the AI compute units, it is part of the solution as the energy requirements can be decreased. This would be beneficial both for the cost of operation of the vehicle as well as for the environment. Additional research is required into thermal imaging to find the exact amount of reduction that could be made to the AI compute units on autonomous vehicles.

In conclusion the use of infrared imaging in autonomous vehicles can mitigate some of the issues that current autonomous vehicles have. Though future research must be done to increase the safety of autonomous vehicles on the roads, I believe that my research is a good first step to having safe autonomous vehicles on the roads.

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