# Deep Learning with Radar

PROJECT PLAN

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(example) Figure 1: Proposed Design Diagram

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ex. Table 1: Timeline of proposed work schedules for the Spring semester.

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# List of Definitions

Please include any definitions and/or acronyms the readers would like to know.

example: ASA: American Standards Association

# 1 Introductory Material

#### 1.1 ACKNOWLEDGEMENT

The project team would like to thank Michael Olson from Danfoss Power Solutions for his support on this project. We would also like to thank Dr. Wang for advising our team.

#### 1.2 PROBLEM STATEMENT

As the agriculture and construction industries require autonomous solutions for increased safety and productivity the need to sense objects in the equipment path increases. There are many solutions on the market today using cameras and LIDAR. These solutions have limitations in weather and low light conditions. We were tasked with creating a system using RADAR to eliminate these limitations.

Our project consists of two main components: the implementation of a RADAR system and the development of a deep learning model. The RADAR system will allow us to detect objects in low-light and bad weather conditions. The deep learning model will identify objects in the equipment's path.

# 1.3 OPERATING ENVIRONMENT

The operating environment for the system will be on agriculture and construction equipment. This will require the system to be able to withstand water and dust from the operating environment and the vibrations associated with operating this equipment.

# 1.4 Intended Users and Intended Uses

The intended use is for certain agricultural vehicles and construction equipment that are a key area for our client.

## 1.5 Assumptions and Limitations

## Assumptions:

The operating conditions for the equipment will be normal and not abusive.

#### Limitations:

The system will only operate up to 35 mph. This will cover a large range of equipment, but not all equipment.

# 1.6 Expected End Product and Other Deliverables

For this project, our deliverables are a RADAR system and deep learning model. The RADAR system will work with the deep learning model for a demo on a piece of construction or agriculture equipment for our client.

# 2 Proposed Approach and Statement of Work

#### 2.1 OBJECTIVE OF THE TASK

Our objective is to evaluate various radar technologies for Danfoss and through a combination of digital signal processing and deep learning, perform object detection and localization. By December 2018, we will have selected a radar option, a computing system adequate for a rough environment, designed and trained a neural network with data collected from the radar system, and implemented it on a vehicle to alert an operator of the presence and location of unique objects.

In order to provide value to Danfoss, we will also include a report evaluating various radar technologies, deep learning platforms, and computing systems to assist them in making a business decision when deciding to implement this technology in the future.

# 2.2 FUNCTIONAL REQUIREMENTS

- 1. The system shall have a range of 60 meters.
  - a. Rationale: A range of 60 meters is required for early detection and identification. A machine traveling at 35 mph will cover 60 meters in 3.8 seconds. This range is allows for an object to be detected with sufficient time for action.
- 2. The system shall function on machines travelling at up to a speed of 35 mph or 15.65 m/s.
  - a. Rationale: Most agriculture and construction equipment travels at speeds in the range of 5 mph to 40 mph. A max speed of 35 mph will allow for the majority of applications to be covered.
- 3. The system shall have angular range of  $\pm 30^{\circ}$ .
  - a. Rationale: An angular range of  $\pm 30^{\circ}$  is required to detect objects in the vehicle's path with sufficient time to stop.
- 4. The system shall have a processing speed of 15 frames per second.
  - a. Rationale: The system needs to detect an object with sufficient time to react. A frame rate of 15 frames per second on a vehicle traveling approximately 35 mph or 15 m/s means the vehicle will travel no further than 1 m between each frame update.
- 5. The system shall detect objects greater than 0.4 m size.
  - a. Rationale: A width of o.4 m is the width of human shoulders. Detection of a human is, at minimum, required for safe operation of the system.

- 6. The system shall be weather resistant to water, dust, and shock.
  - a. Rationale: Danfoss' target applications involve heavy machinery that works in tough environments.
- 7. The system shall have a probability of missed detection less than 0.3.
  - a. Rationale: A probability of 0.3 means that for each subsequent frame, the probability of missing an object multiple times approaches zero, which will yield a sufficiently short stopping distance.
- 8. The system shall have a probability of false alarm less than 0.3.
  - a. Rationale: A false alarm, though undesirable, will be a safer alternative than a missed detection.
- 9. The system shall run off of a 12V power supply.
  - a. Rationale: This voltage is easily available from a selection of batteries with also a range of amp hours. It is also easily available on a heavy equipment chassis. A step-up converter or inverter is acceptable.
- 10. The system shall fit inside i'xi'xi' space.
  - a. Rationale: Space is limited on a vehicle, so our design must be compact enough to not obstruct operator view or regular vehicle operation.
- 11. The system shall detect at least 4 classes of objects.
  - a. Rationale: Our system should detect people, cars, construction equipment, and buildings.
- 12. The system shall/should operate in the temperature range from -40 to 125 degrees Fahrenheit.
  - a. Rationale: This is a common operating range for automotive sensors.

## 2.3 Constraints Considerations

As part of the project, we must evaluate various radar options, deep learning platforms, object detection networks, and computing systems. Evaluation of these systems will be centered around the functional requirements, but the behaviour of the full system cannot be known without implementing all combinations of each option. Therefore, a written report regarding behaviour of individual components is necessary to justify our choices.

Because this project will ultimately lead to a business decision from Danfoss, cost of the system must be considered. We will strive to minimize cost, but not at the expense of our functional requirements.

Our code must be well commented and accessible to the client. The team will use Gitlab for version management of our software. This includes our neural network, data acquisition tools, and any low-level radar code.

Training data acquired during our project must be accessible to our client, yet secure. We will collaborate with Danfoss to ensure data collected (which may include imagery from their facilities) is secure to their internal standards.

For our code, group members will follow an agreed upon coding convention. Because we expect much of our code to be Python, we will follow PEP 8 - Style Guide for Python Code: https://www.python.org/dev/peps/pep-ooo8/.

The IEEE code of ethics will help guide our project, and ensure that our work does not violate the health and safety of our members, equipment operators, or Danfoss employees. We will ensure that any research performed is well documented and cited where necessary. This code of ethics is applicable to our project because we are working on something that may eventually be used to prevent injury, so ethical violations could indirectly cause harm eventually.

## 2.4 Previous Work And Literature

Literature surrounding the use of deep learning with radar focuses on either close-range object classification, or improvement of synthetic aperture radar.

A study from the University of St. Andrews showcases how a short range radar can be used to differentiate between various objects, as shown here:

https://sachi.cs.st-andrews.ac.uk/research/interaction/radarcat-exploits-googles-soli-rada <u>r-sensor-for-object-and-material-recognition/</u>. This study is encouraging in that it shows how radar waves may be reflected in a unique way from different objects, but it does not show long-range applications, which is a significant shortcoming.

A research paper from Radar Conference [1] shows how deep learning can be used to improve the digital signal processing aspect of radar for synthetic aperture radar. This is beyond the scope of our project, as our project centers more around performing deep learning on radar imagery, rather than creating the imagery itself. Also, our system must perform real-time detection, not reconstruct an image later.

Literature more relevant to our project is related to object detection on RGB imagery. Several methods have been published that detail balances between speed and accuracy of neural networks for object detection. This website provides a summary of various object detection methods that we may utilize for our project:

https://towardsdatascience.com/deep-learning-for-object-detection-a-comprehensive-revi

ew-73930816d8d9. Of interest are Single-Shot Detector (SSD) (arXiv:1512.02325 [cs.CV]) and Faster RCNN (FRCNN) (arXiv:1506.01497 [cs.CV]). These network topologies take different approaches to detect objects. FRCNN proposes regions where an object might be, and evaluates each region to determine where an object lies in an image. SSD analyzes an image with fixed bounding boxes around what the CNN determines are relevant features to determine where an object is. For our purposes, SSD may be a better option to explore due to its improved speed compared to FRCNN, but at the expense of accuracy. Both network topologies deal with image resolutions beyond what our radar is likely capable of producing, so we may need to explore techniques for interpolation.

As a team, we must develop a network that can perform object detection in real time with sufficient speed and accuracy that does not rely on these existing networks. Because the data we collect is processed to produce an image, we have the advantage of the option to incorporate raw signal data into our network, which is not an option for state of the art object detection networks for imagery.

## 2.5 PROPOSED DESIGN

In the end, our designed system must be able to detect and identify an object up to 50 meters away, as long as the object is within the 60 degree angle of view. The radar or radars that we will use is still being chosen, as there are a lot of options available.

The system must be able to identify the object. For example, is the object a horse, bale of hay, a human being, etc. For object identification, the deep learning model we are using is called Keras.

The system must be able to operate in all normal weather conditions such as cold, hot, windy, rainy, etc. Again this affects which radar our team will choose.

#### 2.6 Technology Considerations

Many different radar systems and deep learning models are available. It has been decided that Keras is going to most likely be the deep learning model for our system due to its simplicity and because a team member already has experience with this model.

At the moment, the radar system by Walabot is being used as a test subject. This radar system does not have the range needed to meet design requirements, but it does come with an interface that is simple to operate. This system is being used as a testbench so that we can write scripts to convert radar data into distance and angle.

Texas Instruments offers a chip and another supplier has a radar system that mees our distance requirements but does not offer an interface. Also, the system is quite expensive and exceeds our client's budget.

Again, due to the variety of radar systems in the market, a final decision has yet to be made on which radar system our team chooses.

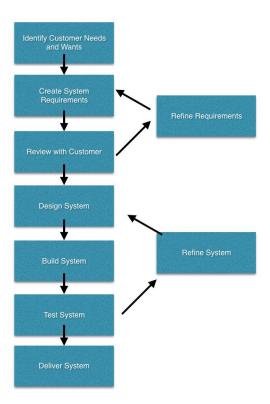
# 2.7 SAFETY CONSIDERATIONS

If soldering circuitry becomes a task, burns are a possible risk. Typical solder temperatures range from 500-800 degrees fahrenheit. The team member attempting to use a soldering station should have basic knowledge on how it operates.

Our design will eventually be tested on large machinery which will create safety risks. Personal protective equipment (PPE) and/or training may be required in order to avoid cuts, head trauma, slips, etc.

#### 2.8 TASK APPROACH

Our task approach for the design can be visualized using the block diagram below. As of now, we have met with the client and determined system requirements. Next, the team will be reviewing those requirements and designing the system. Once the radar system, user interface, and radar chip has been selected, the design process of the overall system will be begin.



# 2.9 Possible Risks And Risk Management

The cost of a radar system can be quite pricey. There is a possibility that our radar selection with exceed our client's budget of \$5000. Another possible reason for the design process to be slowed could be due to the variety of radar systems available. Analysis of many radar systems will have to done to determine which would be the best option. Lastly, our team has a good idea of how the design will be implemented, but at this moment, we have not conducted enough research to be 100 percent confident in our design.

#### 2.10 Project Proposed Milestones and Evaluation Criteria

Deciding on a particular radar system is our first key milestone. The next milestone will be interpreting our radar data to create a deep learning model. The last key milestone will be a working deep learning model. We will know the radar system works if it gives us accurate data to do the deep learning. Our final product will be tested on our client's test track in Ames. If our product detects the object it is supposed to, then we know it works.

#### 2.11 PROJECT TRACKING PROCEDURES

Our group is using GitLab and google drive to track our process.

#### 2.12 EXPECTED RESULTS AND VALIDATION

Our desired outcome is to be able to detect objects such as a human, animals, and other objects in heavy equipment paths. Not not only do we want to detect these objects, but we want the driver to be able to see where the object is and what the object is via a user interface. Again, we will confirm our system works at a high level by testing it at the Danfoss' test track.

# 2.13 TEST PLAN

We will have many different levels of testing. Some testing with be just software testing of the deep learning model. Some will be bench testing of the radar system. We will have some full system testing in a lab environment Lastly. we will take our system to Danfoss' test track for a real world test. We will test the system with objects at 10, 20, 30, 40, and 50 meters. We will test the system with objects moving at various speeds, along with the machines speed.

# 3 Project Timeline, Estimated Resources, and Challenges

# 3.1 PROJECT TIMELINE

Sprint #	Dates	Deliverables
1	01/08 -	Schedule and Roles: We will be solidifying our schedule, roles, responsibilities, and allotting times for meetings. We will be discussing individual positions and we will be assigning tasks and deadlines for specific portions of the project.
2	01/22 -	Target parameters, system requirements, and website: We will be working on improving our website. We will continue to updates documents and responsibilities, which will be published. We will compile a "system requirements" to know what hardware we require to run processes. We will also be solidifying our choice for Radar during this time so we may begin testing.
3	02/05 - 02/18	Final Selections: Our team will have decided on which radars are suitable, the deep learning platform, and what kind of system on a chip (SOC) we will be using as our onboard computer. Once selected, we can begin the testing process to narrow down a final combination of the three components.
4	02/19 - 03/04	Testing: In this portion of our project, we will actually begin to run tests on our final radar/platform/SOC combination to see how it fares and to see if the real world results are what we expected. If our expectations are met or exceeded, we will proceed and begin to prep out deep learning model and run identification tests.
5	03/05 - 03/25	Final Radar and SOC selected: This is the two week slot we have allotted in case we need to rethink our radar/platform/SOC combination. If we are satisfied with our primary combination then we will use these two weeks to begin training.
6	03/26 -	Database of Radar Images: As we approach the end of our semester, the team will start collecting data and classifying it to run it through our deep learning platform so we can identify various radar signals as objects
7	04/09 -	Deep learning model: Once the database is complete we will run it through the deep learning model we selected. When it is ready, we can begin to load it onto our SOC to test it with real objects in front of it.
8	04/23 - 05/04	Port data from radar to deep learning model: We will send the collection of data from the radar to the SOC to be run through the neural network. This way we can improve the accuracy of the net while building a bigger database.

## 3.2 FEASIBILITY ASSESSMENT

We know of some major aspects where we know to be careful. We need to ensure that we remain within the scope of the project. We only want to focus on getting the deep learning model and the radar to work. If we begin to spend too much time on alternative forms of detection, we will be in over our heads. Therefore, we must implement and follow strict constraints.

Our radar and SOC also need to be feasible. To achieve this, we are choosing the most economically sound option for our project. We do not want to cut corners and choose cheap products, but at the same time we also do not want to be spending tens of thousands of dollars and hundreds of hours into the project. Along the way, we will consult our faculty advisor, client, and team members to ensure the products we choose are of the best quality with the most reasonable price tag.

## 3.3 Personnel Effort Requirements

This information is found on our <u>GitLab page</u>. There are dates, assignees, and details all listed out the Issue Board section of out Git.

## 3.4 OTHER RESOURCE REQUIREMENTS

We will need to know how radars work. We will also need to understand how deep learning neural nets work, as well as how to use them with Python. For all of this information, we will be using YouTube, textbooks, and how-to books (ie. "For Dummies" series) as resources. We will also require some storage space, such as a server, for all the test data we use and collect.

In addition to this, when we are close to the end of our project, we will need heavy equipment and a test area to see how our technology fares in the real world.

## 3.5 FINANCIAL REQUIREMENTS

We will be needing to purchase a radar and a controller to go with it. We will also require funding for the server if we need it. Our major expenses are the radar unit itself and the controller.

# **4 Closure Materials**

#### 4.1 CONCLUSION

Our project is to develop a system for Danfoss to use on machinery such as tractors, loaders, excavators, and other heavy equipment that can use radar to detect objects. We will be utilizing deep learning to recognize objects in order for these vehicles to determine if there is a hazard in range of the radar.

We will be choosing to use either a purchased radar and antenna, or develop our own products to meet the system requirements for this project. We hope to create a device that we can put into testing on Danfoss' test track in Ames in order to show leadership and engineers from Danfoss the work we have accomplished and the system we have created.

Our plan is to pick whether we will be developing our own products or purchasing a radar and/or antenna from another company to connect to these machines. Then with our collected data from this radar use deep learning to help decipher whether the objects in the view of the radar are a hazard or are not a hazard.

With all of this accomplished we will have tested a new technology for Danfoss. This technology can help make safer working conditions and future autonomous operation possible. Hopefully, this technology will be feasible for future development into a product for our client.

# 4.2 REFERENCES

- [1] E. Mason, B. Yonel and B. Yazici, "Deep learning for radar," 2017 IEEE Radar Conference (RadarConf), Seattle, WA, 2017, pp. 1703-1708. doi: 10.1109/RADAR.2017.7944481
- Stewart, Louis. "RadarCat for Object Recognition." SACHI, sachi.cs.st-andrews.ac.uk/research/interaction/radarcat-exploits-googles-soli-radar -sensor-for-object-and-material-recognition/.
- Van Rossum, Guido. "PEP 8 -- Style Guide for Python Code." Python.org, 1 Aug. 2013, www.python.org/dev/peps/pep-ooo8/.
- Xu, Joyce. "Deep Learning for Object Detection: A Comprehensive Review." Towards Data Science, Towards Data Science, 11 Sept. 2017, towardsdatascience.com/deep-learning-for-object-detection-a-comprehensive-revi ew-73930816d8d9.

# 4.3 APPENDICES