Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

b-it Bonn-Aachen International Center for Information Technology

Master Thesis Proposal

Federated Learning for Object Detection Using 3D Depth Images

Kevin Patel

Supervised by

Prof. Dr.-Ing. Sebastian Houben
Prof. Dr. Robert Lange
Dr. Markus Hammes
Dr. Nikolaus Mayer

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1 Introduction

1.1 Topic of This Thesis

- TODO: Put a story or a very basic scenario here to make the reader understand the problem.

1.2 Relevance of This R&D Project

- Who will benefit from the results of this R&D project?
- What are the benefits? Quantify the benefits with concrete numbers.

2 Related Work

2.1 Survey of Related Work

- What have other people done to solve the problem?
- You should reference and briefly discuss at least the "top twelve" related works

2.2 Limitation and Deficits in the State of the Art

- List the deficits that you have discovered in the related work and explain them such that a person who is not deep into the technical details can still understand them. For each deficit, provide at least two references
- You should reference and briefly discuss at least the "top twelve" related works

3 Problem Statement

- Object detection using multiple modalities has become a topic of increasing interest in recent years. However, despite the wealth of research in this area, there is still a lack of comprehensive analysis and practical implementation of state-of-the-art methods under adverse weather conditions. Therefore, the primary objective of this research project is to provide a thorough analysis and practical implementation of state-of-the-art methods for object detection using multiple modalities, including but not limited to camera, LiDAR, and radar.

- The comparative analysis of the results will include an assessment of the strengths and weaknesses of each approach with respect to existing state-of-the-art methods.

4 Project Plan

4.1 Work Packages

WP1 Literature Study

- WP1.1 Conduct a comprehensive literature review of state-of-the-art methods for object detection under adverse weather conditions using multiple modalities
- WP1.2 Analyze and compare various fusion strategies for exploiting the complementary characteristics of different sensors
- WP1.3 Search for suitable public datasets with adverse weather conditions and multimodal sensors data

WP2 Data Collection and Preparation

- WP2.1 Acquire the necessary datasets for multimodal object detection under adverse weather conditions, such as K-radar, DENSE, and aiMotive
- WP2.2 Develop tools for pre-processing and augmenting the datasets to enhance the performance of the models
- WP2.3 Perform statistical analysis to identify the main characteristics and challenges of the datasets, including data imbalance and class imbalance

WP3 Model Design and Implementation

- WP3.1 Design and implement an existing multimodal object detection architectures that integrates camera, LiDAR, and radar data
- WP3.2 Investigate various fusion strategies, such as concatenation, mixture of experts, attention-based fusion etc, to determine the most effective approach
- WP3.3 Explore deep learning architectures, such as CNNs, RNNs, and Transformers, to improve the performance of the multimodal model
- WP3.4 Optimize the model's hyperparameters and train the model on the acquired datasets

WP4 Model Evaluation and Validation

- WP4.1 Evaluate the performance of the developed multimodal object detection model on the acquired datasets under adverse weather conditions
- WP4.3 Compare the proposed model's results to existing state-of-the-art or baseline methods and analyze the strengths and weaknesses of each approach
- WP4.4 Identify the limitations of the proposed model and suggest possible future improvements

WP5 Project Report

- WP5.1 Write a detailed report that includes the research problem, objectives, methodology, results, and conclusion
- WP5.2 Present the research findings in a clear and concise manner, highlighting the contributions and limitations of the proposed multimodal object detection model
- WP5.3 Discuss possible future research directions based on the outcomes of the study

4.2 Milestones

M1 Literature review completed and best practice identified

M2 Data collection and preprocessing completed, including cleaning and augmentation

M3 Initial model development and testing completed

M4 Evaluation and optimization of the model completed

M5 Final model development and testing completed, including comparison with existing state-of-the-art methods and analysis of strengths and weaknesses of each approach.

M6 Project report completed

4.3 Project Schedule

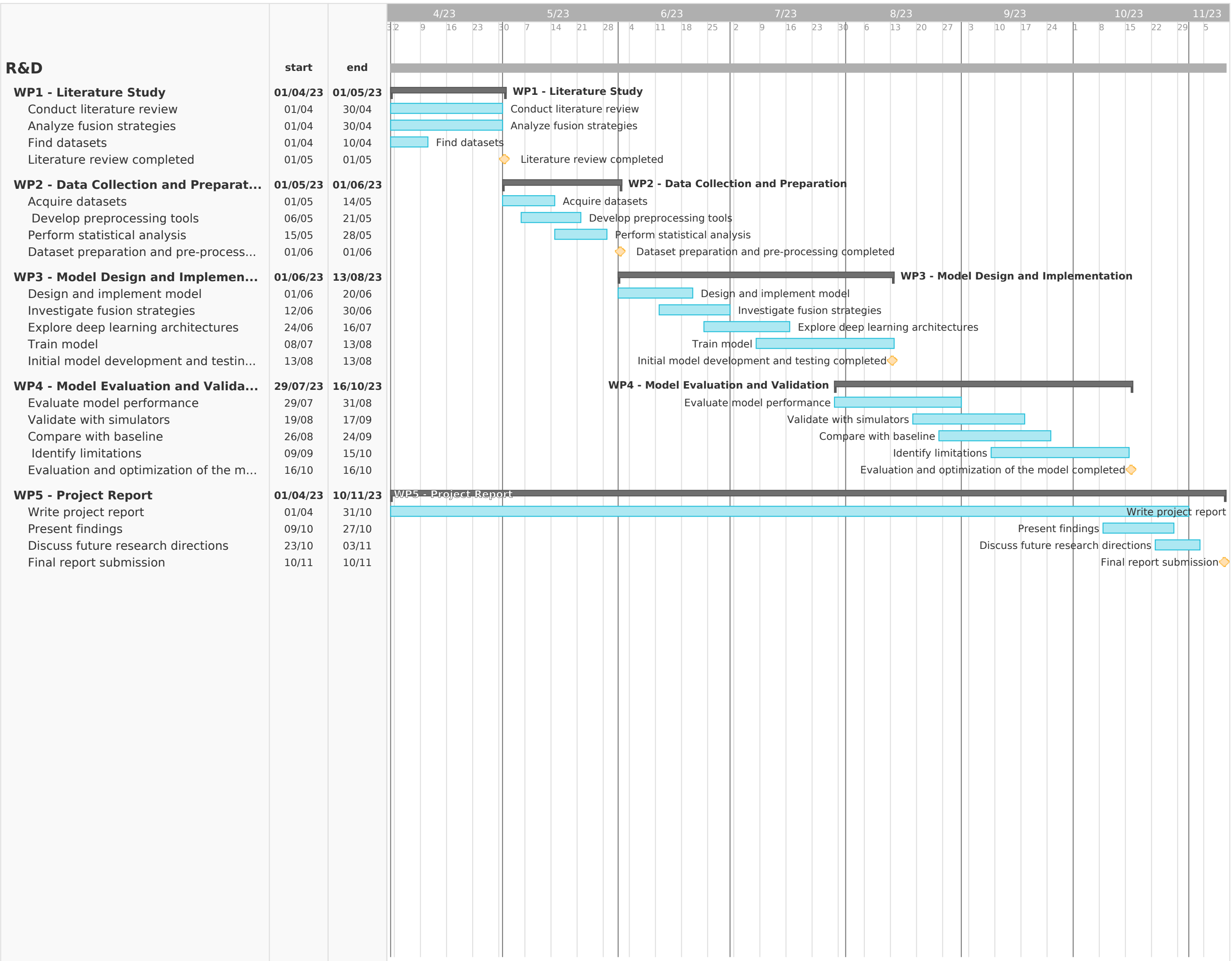

Figure 1: Gantt chart of the project schedule

4.4 Deliverables

Minimum Viable

- Conduct a comprehensive literature review on state-of-the-art multimodal object detection methods and their fusion strategies
- Develop and test existing models for object detection
- Perform a comparative analysis of at least two methods on one dataset
- Produce a project report that summarizes the work done and the results obtained

Expected

- Compare the performance of more advanced methods with the baseline methods
- Complete the final development and testing of the model, including comparison with existing state-of-the-art methods and analysis of the strengths and weaknesses of each approach.
- Produce a more extensive project report that details the methodology, experimental setup, results, and analysis.

Desired

- Compare the developed models' performance on one or more additional datasets.
- Propose improvements to the baseline fusion methods.

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