Orthomosaic Registration Using Tree Segment Features

TREEREG Project Proposal

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1 Project Description

Agriculture is an important factor to a country's economic growth and poverty reduction. The study of successful economic growth in various countries makes it clear that the sustainable development of the agricultural sector is vital [1]. Furthermore, it is estimated that a 25% - 70% increase in crop yield is required to meet the nutrition needs of the world's population in 2050 [2]. Existing farming management practices need to be optimised to reach this goal. The current approach to solve this problem is Precision Agriculture (PA) [3], which is a farming management concept based on observing, measuring and responding to inter and intra-field variability in crops. The goal of which is to maximise crop yield while minimising resource expenditure. The widespread use of sophisticated Unmanned Aerial Vehicles (UAVs) are a driving force behind the viability of current Precision Agricultural practices. This is due to their ability to take high spatial and temporal resolution images of farmland on demand [3]. The images are subsequently processed, aligned and combined to produce orthomosaic maps of a large stretch of farmland, a key input in agricultural analysis applications for PA.

Aerobotics [8], a stakeholder in this project, is a company in the PA field. They provide farmers with information of trends on their farms over time through the analysis of multi-temporal orthomosaic maps of their orchards. An orthomosaic is a high-resolution geometrically corrected aerial image, composed of many individual still images being stitched together [9]. A core functionality of their product is the ability to compare changes in tree performance (on a tree-level) over time. For this to be possible, it is critical that the input orthomosaics are correctly registered. Image registration is the process of correctly aligning two or more images of the same scene. They currently use a semi-automated approach to register these maps, where successive surveys (orthomosaic maps) are registered with previously processed datasets using a human-in-the-loop approach. This reliance on manual intervention in the registration process creates limitations in the scalability of their orchard trend analysis system. As such, a fully automated process to accurately register these input datasets would greatly improve their scalability and operating margins. Automation of the orthomosaic registration process is the crux of this project.

The detection and matching of salient features in the input images is a common approach to registration. Aerobotics have developed a robust feature extractor for this purpose, a tree instance segmentation model. This produces a bounding polygon around individual tree canopies on the map, with an associated confidence level. The main problem presented by this project is the use of this developed feature extractor to automatically and accurately register multi-temporal orthomosaic maps of orchards.

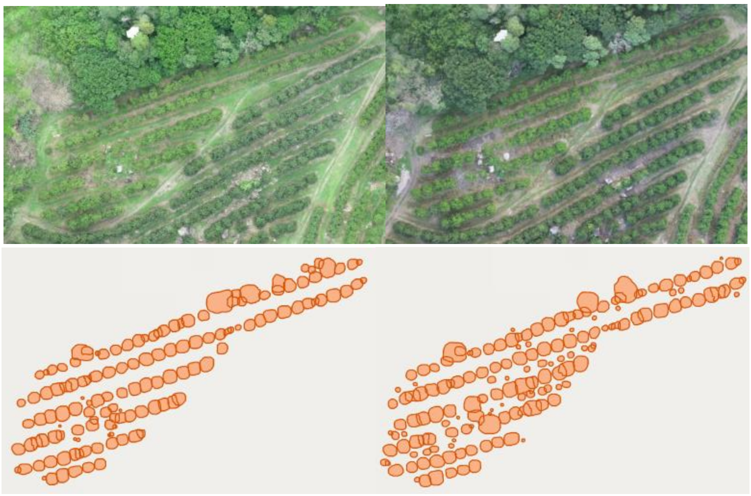


Figure 1: Multi-temporal orthomosaic maps of an orchard (Top) and their corresponding feature detections (Bottom).

2 Problem Statement

The central issue of this project is an investigation into the feasibility of automatic feature-based orthomosaic registration methods. More specifically, the aim of this project is to evaluate the applicability of feature-based registration methods to accurately register multitemporal orthomosaics of orchards for Aerobotics. These feature-based registration methods must make use of the tree polygons produced by Aerobotics' existing tree instance segmentation model as inputs to the registration process.

2.1 Aims

Two feature-based registration methods, one from each team member, will be evaluated on their ability to solve this problem. The primary aim of the project is an in-depth analysis of the applicability of each of these approaches to the problem domain. Each of these approaches share the following additional aims regarding their implementation:

- To be invariant to translational and rotational transformations in each of the input images being registered.
- To produce a result with an acceptable registration accuracy metric (defined later in 3.4).
- To be robust to erroneous tree detections in the input data.

An additional aim of this project is to determine whether the use of a Bayesian network model for advanced feature matching will improve the accuracy of our registration methods.

2.2 Research Questions

Two research questions, from each project member, regarding the two separate approaches to the feature-based registration process are listed below. Details about their individual evaluation are outlined in subsequent sections.

Iterative Closest Point Matching research question:
The main objective of this question is to determine how accurately orthomosaics can be registered when using the Iterative Closest Point (ICP) algorithm [10], with input point landmark generation through Bayesian updates, to produce valid transformation parameters. The evaluation process will be explained in 3.4. The complement of a Bayesian network model will be investigated as an aid to the registration process.

Ant Colony Optimization for Row Matching research question:
The objective of this question is to determine how accurately images can be registered when using the row detection from the Ant Colony algorithm for feature matching [15]. A sub research question is whether the registration can be more accurate by using a Bayesian network model [19] for row matching.

3 Procedures and Methods

The overall architecture of the proposed system consists of 6 modular components, shown in figure 2. Four of these components are individual work as they contain functionality specific to each team member's approach and will be developed in parallel. The other components contain shared functionality. There are two phases to this project, with each phase producing a significant component of the registration system. The first, core phase of the project is the implementation of the registration methods without the complement of a Bayesian network model. The second phase involves the use of a Bayesian network to improve phase 1 registration. The phases will be explained below.

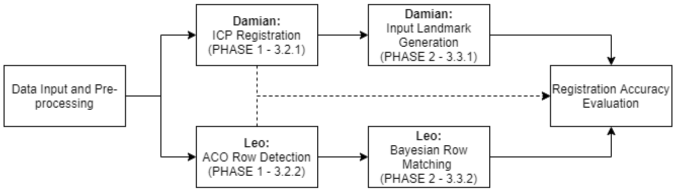


Figure 2: Overall System Architecture

3.1 Data Input and Pre-processing

The input data provided for this project will have to be pre-processed before being used in our registration methods.

3.1.1 Input Data

The data for this project was provided by Aerobotics. The input data provided consists of information about different orchards. Each orchard contains data pertaining to two *surveys* of that orchard: a specific point in time at which a drone captures imagery of the orchard.

Each survey contains the following input files:

- boundary.geojson: A polygon representing the boundary of the orchard in GeoJSON format (this file is the same for both surveys).
- visible_10cm.tif: An orthomosaic of the human-visible image channels (RGB) for the given survey.
- dem_10cm.tif: An orthomosaic of the depth elevation map image channel, an estimate of the depth (or height) at each position.
- raw-detections.geojson: Tree polygon outputs from the instance segmentation model in GeoJSON format. Each contour includes the model's confidence level.

The overall goal of the project is to find methods to accurately register the orthomosaics of the two different surveys of an orchard.

Some pre-processing of the data is required. The coordinates of the tree instance polygon vertices are provided in a Geographic Coordinate System (GCS). This makes any arithmetic calculations, such as centroid and area calculations, unnecessarily complex and expensive. These will have to be pre-processed and converted to a projected 2D coordinate system, i.e.,. from latitude and longitude to pixel x and y coordinates. The input orthomosaics provided have also been pre-registered by Aerobotics. As such, before we can test our proposed registration methods, we will have to misregister them through various rotational and translational transformations. The parameters of these transformations for the misregistering of the input images will be recorded. The purpose of this is to determine how close our registration methods come to reversing these intentional transformations during the evaluation process (see 3.4 for more details). Aerobotics have only provided pre-registered input files, a request for raw data is currently pending. If we can not use raw data, the input data will be misregistered to match their current raw image deformations with the aid of a Gaussian noise algorithm to generate random transformational differences [11].

3.2 Phase 1: Core Functionality

Below we outline the proposed approaches making up the first core phase of the project. Each student will be responsible for one approach to register the pair of orthomosaics.

3.2.1 Iterative Closest Point Based Registration

The ICP algorithm is an established approach to determine the transformation required to align one point cloud (the source) to another (the reference). This is done through iteratively refining the transformation to minimize an associated error metric, which in this case is the Root Mean Square Distance between the points in the source and reference point clouds. The problem of registering orthomosaics based on detected features can be reduced to an optimization problem of minimizing the distance (error) between input point clouds using ICP [10].

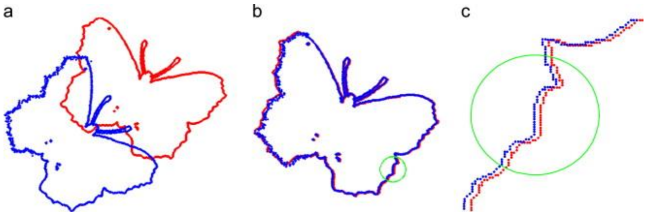


Figure 3: Example of ICP being used to register 2D point-based geometric objects [7]

Firstly, point clouds will be generated from each input image. One point cloud is the reference, and the other is the source, the source cloud will be transformed and overlayed on the reference. The centroids of the detected tree polygons will be extracted and together will form the input point clouds for the ICP algorithm. To improve the efficiency and robustness of the algorithm, only centroids from detections with an acceptable confidence level (>90%) will be used.

The rigid transformation model used to register the source point cloud (from sensed image) onto the reference point cloud (from reference image), to a given degree of accuracy, is refined in an iterative process [10]:

1) First, the source point cloud is placed on to the same 2D plane as the reference cloud.

2) A nearest-neighbour algorithm will then be used to determine the pairs of points (one from each set) with the closest Euclidean distance. These will be the provisional matched pairs for the iteration.

3) A Root Mean Square error metric will be calculated using the Euclidean distances between the paired points. The accuracy of the algorithm depends on the assumption that matched point pairs are presented in both images, none of them are outliers. To ensure this, a threshold parameter must be determined, and any paired points with a distance greater than the threshold will be discarded from the error calculation.

4) The transformation estimation (consisting of rotation and translation) of the iteration must be computed. The rotation matrix (R) and translation vector (t) for the iteration will be computed using a least-squares method for distance minimization between point pairs. A Singular Value Decomposition (SVD) method will be used to determine the rotation and translation parameters in each iteration [13].

5) The points in the source point cloud are then transformed according to this rigid transformation estimation.

6) From here, the next iteration begins, starting at step 1 again. This process will be repeated iteratively until convergence in the estimation of rigid transformation parameters. The final result will be a rotation matrix and translation vector that will accurately register the points in the source cloud to the reference. These parameters can then be used to register the entire input orthomosaic source image.

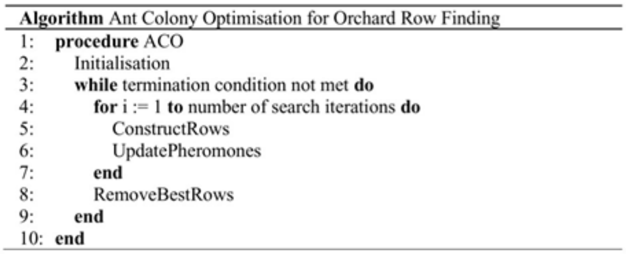
The ICP algorithm is locally convergent, meaning it is unsuitable to register images with significant rotational differences [13]. However, the input images in this project are misaligned slightly between dates, making it a suitable approach. This approach makes use of the overall shape of the features in images to register them, making it robust to the temporally unstable nature of individual trees as features. However, there are significant drawbacks to this approach that could cause it to fail in the registration process due to the nature of the input data. These are discussed in 3.3.1 and a solution for these concerns is proposed.

3.2.2 Heuristic Ant Colony Optimization (ACO) based registration

This approach is mainly based on the heuristic row detection method from [15]. This registration approach has two phases: the first phase is to detect and form shapes (in this case would be rows, each row is a set of tree polygons, rows can be straight or curved) in each image (sensed and referenced) using heuristic ACO algorithm. Then to match rows from two images based on the Euclidean distance between polygons of rows from two images, rows with the minimum Euclidean distance sum will be matched. Phase 2 uses a Bayesian network model to match rows instead of Euclidean distance, which for each date Bayesian network model will be updated and accumulated for next prediction.

This phase focuses mainly on forming rows using the heuristic ACO (Ant Colony Optimization) algorithm proposed in [15]. It interprets the problem of finding rows from polygon detection as finding an optimal path in a graph where each node is a polygon represented by its centroid. It incorporates domain-specific heuristics such as the distance and angle between two nodes. The algorithm is shown in Figure 4.

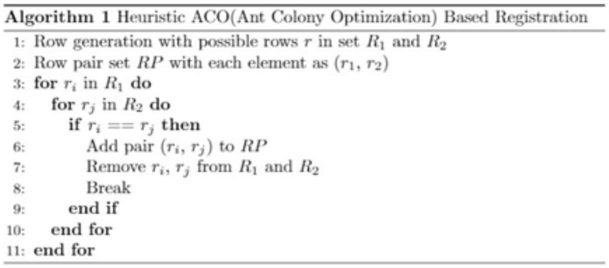
It starts with exploring different paths, for each path searching loop (inner), the ant (program) constructs possible paths based on the distance and angle between two nodes, and then updates the pheromones for each path. A best path with the highest heuristic values will then be selected, the polygons in that row will be removed from the search space for the following loops.



```
Algorithm Ant Colony Optimisation for Orchard Row Finding
procedure ACO
    Initialisation
    while termination condition not met do
        for i := 1 to number of search iterations do
            ConstructRows
            UpdatePheromones
        end
        RemoveBestRows
    end
end
```

Figure 4: Heuristic ACO algorithm

After the row formation, a set of rows will be produced for each image (2 sets in total). For each row in the set 1, all rows in set 2 will be used for matching. Matching is done by considering the Euclidean distance sum between two rows' polygons. Row pairs with minimum distance will be matched. Only some selected polygons will be considered at this stage, for instance the first node, middle node, and final node. The overall algorithm is shown in Figure 5 where r1 and r2 are the "same" when they are matched.



```
Algorithm 1 Heuristic ACO(Ant Colony Optimization) Based Registration
Row generation with possible rows $r$ in set $R_1$ and $R_2$
Row pair set $RP$ with each element as $(r_1, r_2)$
for $r_i$ in $R_1$ do
    for $r_j$ in $R_2$ do
        if $r_i == r_j$ then
            Add pair $(r_i, r_j)$ to $RP$
            Remove $r_i$, $r_j$ from $R_1$ and $R_2$
            Break
        end if
    end for
end for
```

Figure 5: Heuristic ACO registration

This phase guarantees the minimum requirement for registration. A finer registration will be presented in phase 2.

3.3 Phase 2: Bayesian Network Complement

Below we outline the proposed approaches making up the second phase of this project. Each approach will be an extension to one approach in phase 1. The overall goal of this phase is to improve the accuracy of the registration in phase 1 using probabilistic analysis on the provided confidence level of the feature detections.

3.3.1 Bayesian pre-processing of ICP input data for point landmark generation

The success of the ICP registration algorithm is dependent on the accuracy of the input data. A main drawback of ICP is its slow convergence and sensitivity to outliers, missing data and partial overlaps [12]. The input feature segments used in this project are subject to detection error, and as such outliers and missing data between the input detections are expected. Aerobotics' segmentation model derived these detections via a probability map in which each detected polygon has an associated confidence level regarding the accuracy of the detection. An approach to the cleaning of the input data segments for registration, using a novel Bayesian update model, is proposed here. First, a heat-map will be created from the input detections. The colour gradient for the detections will be determined by their associated confidence score (i.e., red for high confidence level and green for low). Then, information about neighbouring segments (adjacent polygons) with relatively high confidence levels (similar high colour gradients) will be extracted. A novel Bayesian network model is proposed to decide whether an input point in each image is a landmark. A landmark is an input point, with a high-confidence level that is present in both input images. The use of landmarks, as opposed to unreliable feature detections, as the basis of feature matching in registration assures the accuracy and robustness of the ICP registration algorithm.

The Bayesian network (BN) model has been proposed to decide whether an input point is a landmark as it is an established method for probability computations using Bayesian inference [14]. The aim of the BN is for it to compute the probability that a given input point is a landmark. It will do this by modelling the conditional dependence between random variables, such as point location, confidence level, confidence level of neighbours. Through inference, the conditional dependencies between the random variables will be determined. Points with a relatively high probability of being a landmark will be used as inputs to ICP (i.e. the top 20%).

3.3.2 Row-Matching with Bayesian Network

This is an extension of the ACO-based registration method in phase 1. For this phase, a Bayesian network model will be used to match rows instead of calculating the Euclidean distance between rows. The Bayesian network model will consider factors such as location, the context, the number of nodes for each row.

3.3.3 Combined Approach for Registration

For this phase, two Bayesian network models [19] will be developed. The first is a bottom-up Bayesian network model that detects landmarks (polygons) from all the polygons. These landmarks will be used for ICP to further improve the registration accuracy.

The second is a top-down Bayesian network model that will be used to match rows instead of calculating the Euclidean distance between rows. This Bayesian network model will consider factors such as location, the context, the number of nodes for each row.

After obtaining two Bayesian network models, two approaches will be combined where the heuristic ACO based approach will provide a set of match rows, ICP approach will take each row pair and match the polygons from each row pair.

It should be noted that each Bayesian network model is accumulated and updated throughout the entire image registration process for every orchard since it tries to register a set of time-series images for a single orchard.

3.4 Registration Accuracy Evaluation

The accuracy of the registration methods is evaluated in two ways, quantitative and qualitative.

quantitative evaluation: The input images provided by Aerobotics are already registered. Therefore, as part of our quantitative evaluation process, we will purposefully deregister them with random translational and rotational transformations. These misregistered images will then be inputted to both our registration methods. The transformation models for registration produced by our methods will be recorded. They will then be compared to the initial transformations we used to misregister the input data. The registration accuracy of our methods can be determined through identifying the level to which they successfully reversed the initial transformations. This metric will be a distance error metric in meters.

The pixel similarity between the transformed images and the preregistered images from Aerobotics will be calculated. This is done through calculating the mean squared error between pixels from two images. The smaller the result, the higher the accuracy, and vice versa.

qualitative evaluation: A visual assessment by students is performed to test the quality of the registration process.

4 Ethical, Professional and Legal Issues

There are no special legal or ethical implications for this project. All the input data used for this project has been freely provided by Aerobotics and may be released publicly. The data is not sensitive or private in nature and does not represent humans in any way possible. The data does contain information about the state of a real farm. However, it has been made clear to us that it is free to use for our research with no restrictions. Any software produced for this project will solely be a proof-of-concept of the registration techniques proposed. It will be open source. Therefore, there are no ethical, professional or legal issues in this project.

5 Related Work

5.1 Image Registration

Image registration approaches are categorized into two categories: area-based and feature-based image registration [5]. For area-based methods, windows of predefined size or the entire image are used to calculate the similarity between two images. Window pairs with the highest similarities are matched and the transformation model is estimated from those matches.

Most of the feature-based image registration approaches rely on SIFT or its variations due to its outstanding feature invariances to scale and rotation. It uses scale-space to detect feature points (which makes them scale invariant) and localize those feature points to get more consistent feature points [4]. Orientation is then assigned to each feature point to achieve rotation invariant. Feature points are represented as special feature descriptors so matching feature points can be easily achieved. Feature-based registration will be used in this project using the tree segment detections.

Unfortunately, due to the changes, deformations and shifts in landscape that occur in orthomosaic images taken at different times, feature points detected by SIFT can contain many outliers. These can lead to poor registration accuracy. For the same reason, window pairs are often mismatched for area-based methods, resulting in erroneous transformation models.

5.2 ICP-based Registration

ICP-based registration is a widely used method for point-cloud registration. It is often used for determining the rigid transformation parameters to register 2D or 3D point clouds using invariant features [17]. However, a key difference in it’s application in this project is that the features being matched (trees) are not invariant. They are subject to growth and deformation over time. Therefore, we propose the use of a Bayesian Network to generate relatively invariant landmarks as input points. Many variations of the ICP algorithm have been developed to compensate for it’s many drawbacks: In [13], they proposed a new, robust variation of ICP that is invariant to any rotational differences, traditional ICP methods often fail when the inputs have significant rotational deformations. If the input data presents similar issues, a similar approach can be taken. In [18], a new approach to ICP using global iterative distance optimization as opposed to the standard local method was presented. This vastly improves the robustness of the algorithm as it enables a successful registration despite the initialization. Standard ICP algorithms are susceptible to local minima during the optimization process and thus rely on the quality of the initialization for their success. If the input data presents significant initial differences between the images, a similar approach can be used. Many approaches to increasing the efficiency, speed and reducing the number of iterations in ICP have been developed. These include the use of data-structures like k-d trees, intermediate point matching and point weighting [10]. However, speed and efficiency are not the main concern of this project, this is a proof of concept so efficiency optimizations will not be focused on unless necessary during the testing process.

5.3 Ant Colony Optimization (ACO)

Ant colony optimization algorithm was proposed in [16]. It was inspired from ant’s behaviour of searching for food. When an ant searches for food, it will leave pheromones on its way. After it reaches the food, it carries as much as it can and goes back to its nest. Along the way it will leave pheromones depending on the quantity and quality of food. Different ants will follow different paths, but paths with more pheromones will have a better chance for ants to follow it. The algorithm is based on a similar idea where at first the program explores different paths and depending on the quality (user defined), adjusts the probability weighting between different paths. After some iterations, an optimal path (with the highest probability) can be found. In [15], the author has proposed a heuristic ACO algorithm for solving row detection problems which has shown promising results. This structure can be used for matching and registering images.

6 Anticipated Outcomes

The major result of this project is an in-depth analysis of the applicability of the two novel proposed approaches to orchard orthomosaic registration for Aerobotics. A software solution will be developed as a proof-of-concept for these proposed approaches, as well as to evaluate their effectiveness in the problem domain. The software solution will consist of the 6 components of the overall solution architecture outlined in section three. The key features of the proposed software solution would be the successful registration of the input images and the subsequent evaluation of the registration accuracy.

6.1 Expected Impact of the Project

We aim to introduce a new paradigm in the area of feature-based image registration. Previous feature-based registration methods require that the detected features be invariant through time. This is not the case in this project, due to the inherent temporally unstable nature of trees. Tree canopies can change in shape over time, changing their associated polygon generated by the feature extractor. Therefore, this project introduces new approaches to feature-based registration using temporally unstable features. These new approaches may yield greater accuracy than previous registration approaches in similar problem domains. The success of this project may also impact the existing registration process at Aerobotics. If the methods proposed here are shown to produce a suitable level of accuracy in registration, similar techniques might be employed in the company.

6.2 Key Success Factors

The following are key factors for the success of this project:

- A sufficient level of understanding of our proposed approaches for their successful implementation in the problem domain.
- The registration methods should be computationally feasible. This is so that they are applicable to real world applications and that our experiments produce enough results, on our machines and in our time frame, for successful analysis.
- An accurate and feasible evaluation method for the accuracy of the registration methods must be developed. The accuracy of the registered image should be in an easily interpretable format e.g., a confidence interval of registration error in meters.
- The implemented registration methods must be fully automated.
- The implemented registration methods should produce accuracy levels comparable to the current approaches used by Aerobotics.
- A successful implementation of a Bayesian network to aid the feature matching process of the registration methods.

7 Project Plan

The following is a detailed plan about the execution of this project.

7.1 Risk

The potential risks with their mitigations, monitoring and managements associated with the project is shown in the following risk matrix (check appendices).

7.2 Timeline

The project starts on 3rd of May and concludes on 18th of October. Due to the COVID-19 pandemic, the dates are subject to change. See the attached Gantt Chart in appendices.

7.3 Resources required

The following resources are needed for completing the project:

Equipment:

- Two good computers for each team member, must be capable of efficiently running the proposed algorithms.
- Access to UCT high speed computer, if necessary.

People:

- Two Computer Science Honours students - Leo and Damian.
- Aerobotics representative - Wasim Lorgat. He will provide data and requirements.

Software:

- Python3 - This is the development language all software will be built on [20].
- Javascript (specifically the D3.js library) - This will be used to visualize the geospatial data (i.e., the tree polygons [21]

Python Libraries:

- Fiona - for reading and writing georeferenced data [22].
- Numpy [23] and Scipy [24] - for manipulating multidimensional data (i.e., pixel data of the images).
- Bayespy - for constructing a Bayesian network model [25].
- Affine - for converting geographical coordinates to 2D pixel x and y coordinates [26].

- Shapely - for working with geometric objects (tree contours). Can be used to calculate area and centroids of the detected polygon [27].

7.4 Deliverables

The major project deliverables include:

- Literature Survey
- Project Proposal
- Project Presentation
- Project Paper
- Project Code
- Poster
- Web Page

7.5 Milestones

The major milestones for the project are as following:

- Literature survey submission
- Project proposal submission
- Project presentation submission
- Initial project feasibility demonstration
- Revised project proposal submission
- Finish evaluation script
- Algorithms achieve 70%, 80%, 90% or 95% registration accuracy.
- Project code submission
- Project paper submission
- Final project demonstration
- Finish poster
- Finish web page

7.6 Work Allocation

Damian and Leo will develop the data-processing component (3.1) together. From there we will implement our respective approaches in parallel. Damian will implement both phases of the ICP based registration method (3.2.1 and 3.3.1). Leo will implement both stages of the ACO based registration method (3.2.2 and 3.3.2). And finally, Damian and Leo will develop the registration accuracy evaluation component together (3.4). Damian and Leo will write separate project reports about the analysis and implementation of their respectful approaches.

All other written artifacts produced by the project will be done by Damian and Leo together, equally. All shared deliverables (i.e., poster, webpage etc.) will be worked on equally too.

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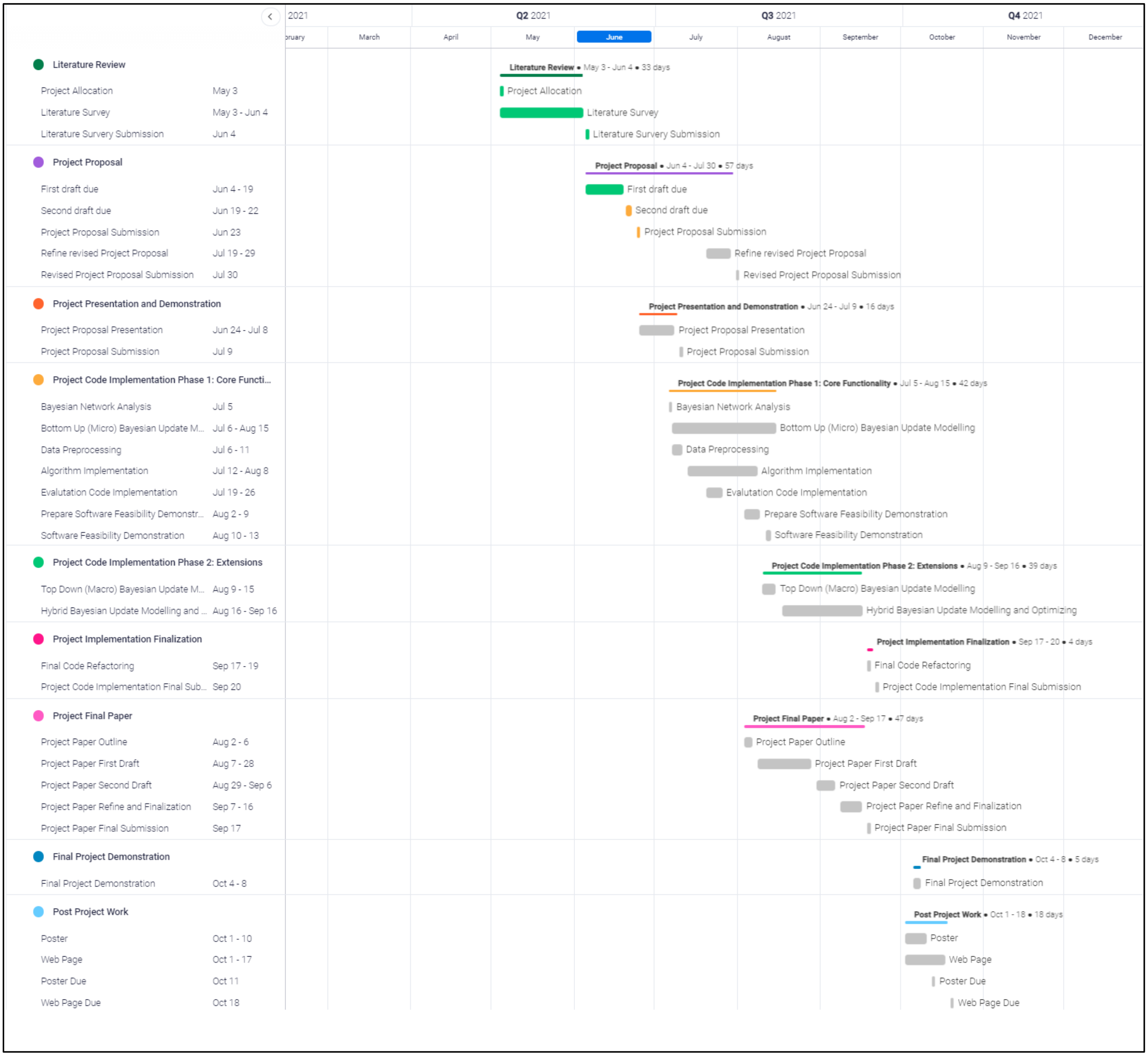
Appendix

Risk Matrix :

<u>**Risk Condition**</u>	<u>**Consequence**</u>	<u>**Probability (out of 10)**</u>	<u>**Impact (out of 10)**</u>	<u>**Mitigation**</u>	<u>**Monitoring**</u>	<u>**Management**</u>
Delay in obtaining dataset	Cannot properly evaluate the algorithms	7	3	Periodic communication with Aerobotics	Track the response and dates	Contact Aerobotics to get the data ASAP
Hardware Deficiencies	Team members cannot work on the project for a period of time	3	9	Consistent communication between team members to update each other of what is going on	Check state of members' devices	Schedule planning to spend long periods in the lab
Fail to meet deadlines	A delay in overall progress of the project	6	8	Overestimate time taken for each task, decrease project scope, set reasonable deadlines and goals	Keep track of deadlines and set up deadlines for each task	Focus on the core components, adjust expectation and goals
Complexity of the selected algorithms are too high	Delay of the project may follow	7	9	Periodic communication with supervisors to make sure the feasibility of the algorithms	Keep track of the progress for each algorithm	Switch to a new algorithm, simplify the algorithm or adjust the deadlines
Selected algorithms may not be able to solve the problem at a satisfactory level	The resulting registration would have bad accuracy	9	9	Detailed analysis of the algorithm should be performed to evaluate the algorithm		Implement a new algorithm or improve the current algorithm

Gantt Chart :



Literature Review	
Project Allocation	May 3
Literature Survey	May 3 - Jun 4
Literature Survery Submission	Jun 4
Project Proposal	
First draft due	Jun 4 - 19
Second draft due	Jun 19 - 22
Project Proposal Submission	Jun 23
Refine revised Project Proposal	Jul 19 - 29
Revised Project Proposal Submission	Jul 30
Project Presentation and Demonstration	
Project Proposal Presentation	Jun 24 - Jul 8
Project Proposal Submission	Jul 9
Project Code Implementation Phase 1: Core Functi...	
Bayesian Network Analysis	Jul 5
Bottom Up (Micro) Bayesian Update M...	Jul 6 - Aug 15
Data Preprocessing	Jul 6 - 11
Algorithm Implementation	Jul 12 - Aug 8
Evalutation Code Implementation	Jul 19 - 26
Prepare Software Feasibility Demonstr...	Aug 2 - 9
Software Feasibility Demonstration	Aug 10 - 13
Project Code Implementation Phase 2: Extensions	
Top Down (Macro) Bayesian Update M...	Aug 9 - 15
Hybrid Bayesian Update Modelling and ...	Aug 16 - Sep 16
Project Implementation Finalization	
Final Code Refactoring	Sep 17 - 19
Project Code Implementation Final Sub...	Sep 20
Project Final Paper	
Project Paper Outline	Aug 2 - 6
Project Paper First Draft	Aug 7 - 28
Project Paper Second Draft	Aug 29 - Sep 6
Project Paper Refine and Finalization	Sep 7 - 16
Project Paper Final Submission	Sep 17
Final Project Demonstration	
Final Project Demonstration	Oct 4 - 8
Post Project Work	
Poster	Oct 1 - 10
Web Page	Oct 1 - 17
Poster Due	Oct 11
Web Page Due	Oct 18