LIDAR LOCALISATION IN UNSTRUCTURED ENVIROMENTS

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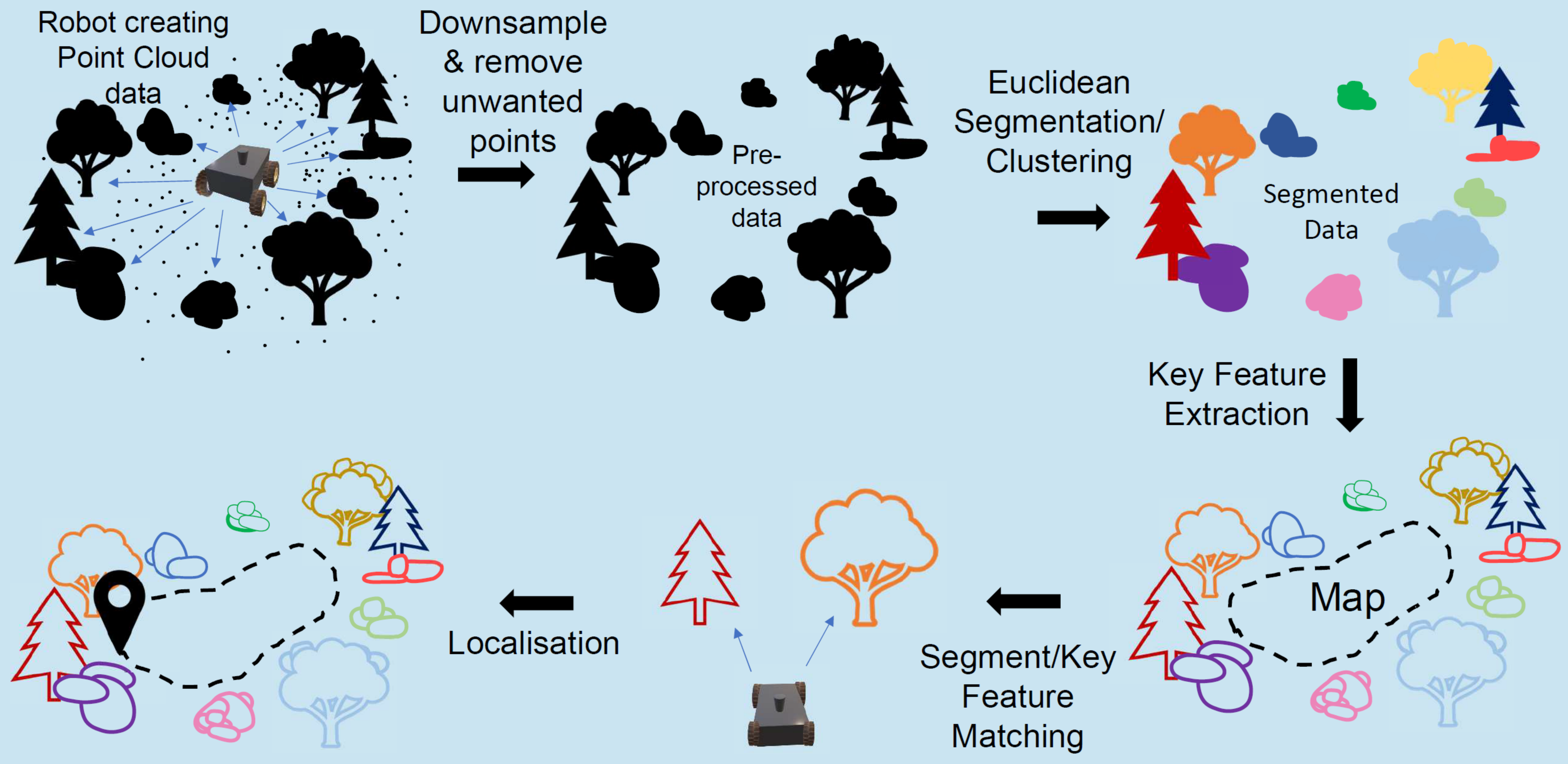
PROBLEM STATEMENT

"Robots and autonomously navigating vehicles have made significant progress in using LiDAR data, localisation and mapping in urban and structured environments, however, little research and development has been attributed to unstructured environments, where key environmental structures and features are difficult to identify, process, and utilise for place recognition."

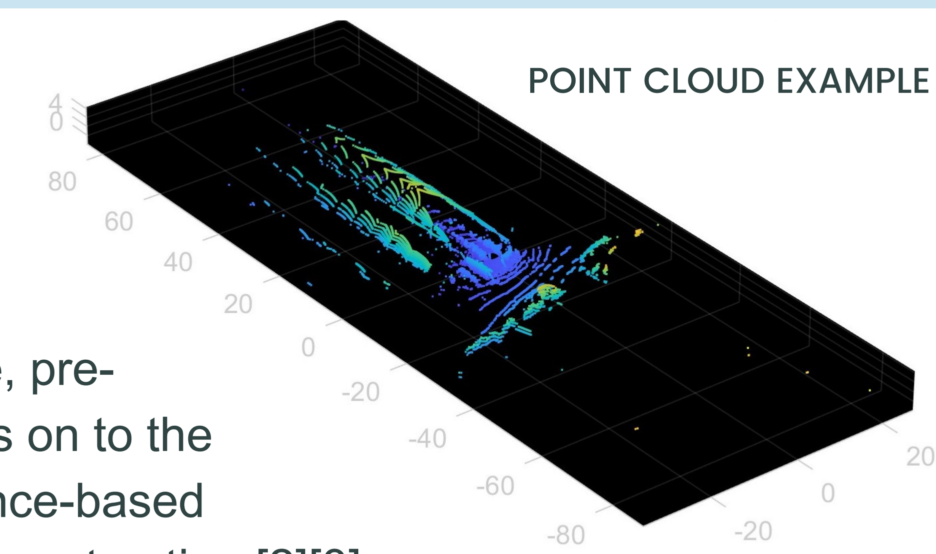


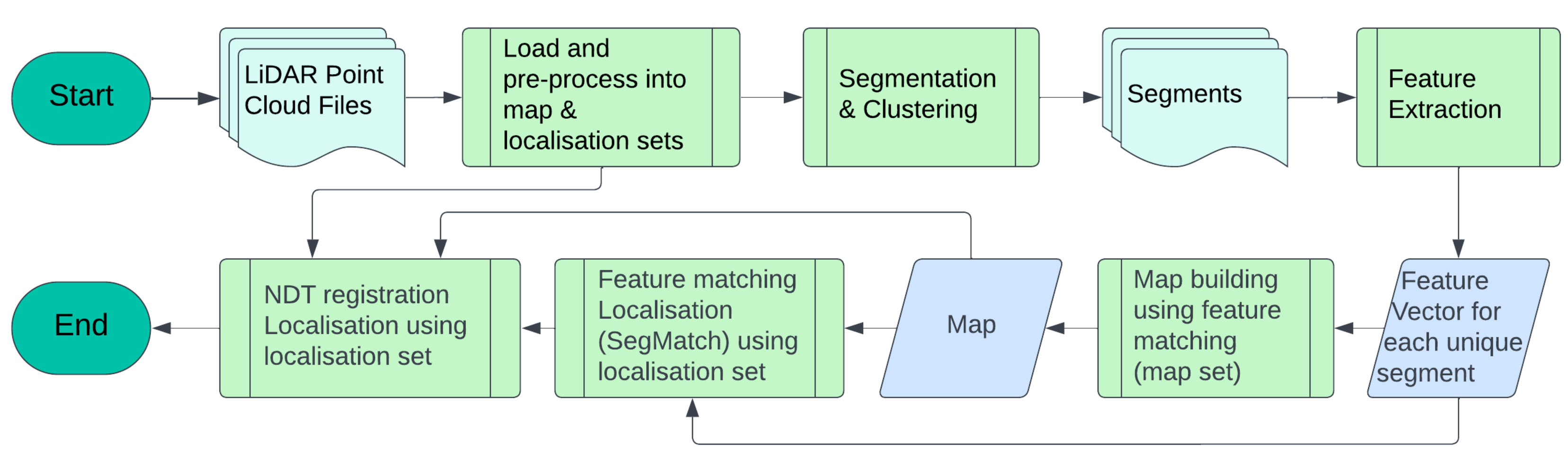
OBJECTIVE

The overarching aim of the project is to enable the Husky robot, equipped with a LiDAR sensor, to build a map and identify where on the map it lies, based on key elements it sees around it at a point in time. The outcome of this project is the development of a data processing pipeline necessary for the processing of the LiDAR point cloud data, to enable the Husky to localise itself in unstructured enviroments.

DESIGN

The design began with an investigation into the C++ library, Point Cloud Library, and the open-source SegMatch [1]. Limitations and the absence of a ROS-based system necessitated the change in approach to using MATLAB. After investigations into each aspect of the final sequence for processing, and changing and testing different parameters, the pipeline was finalised.





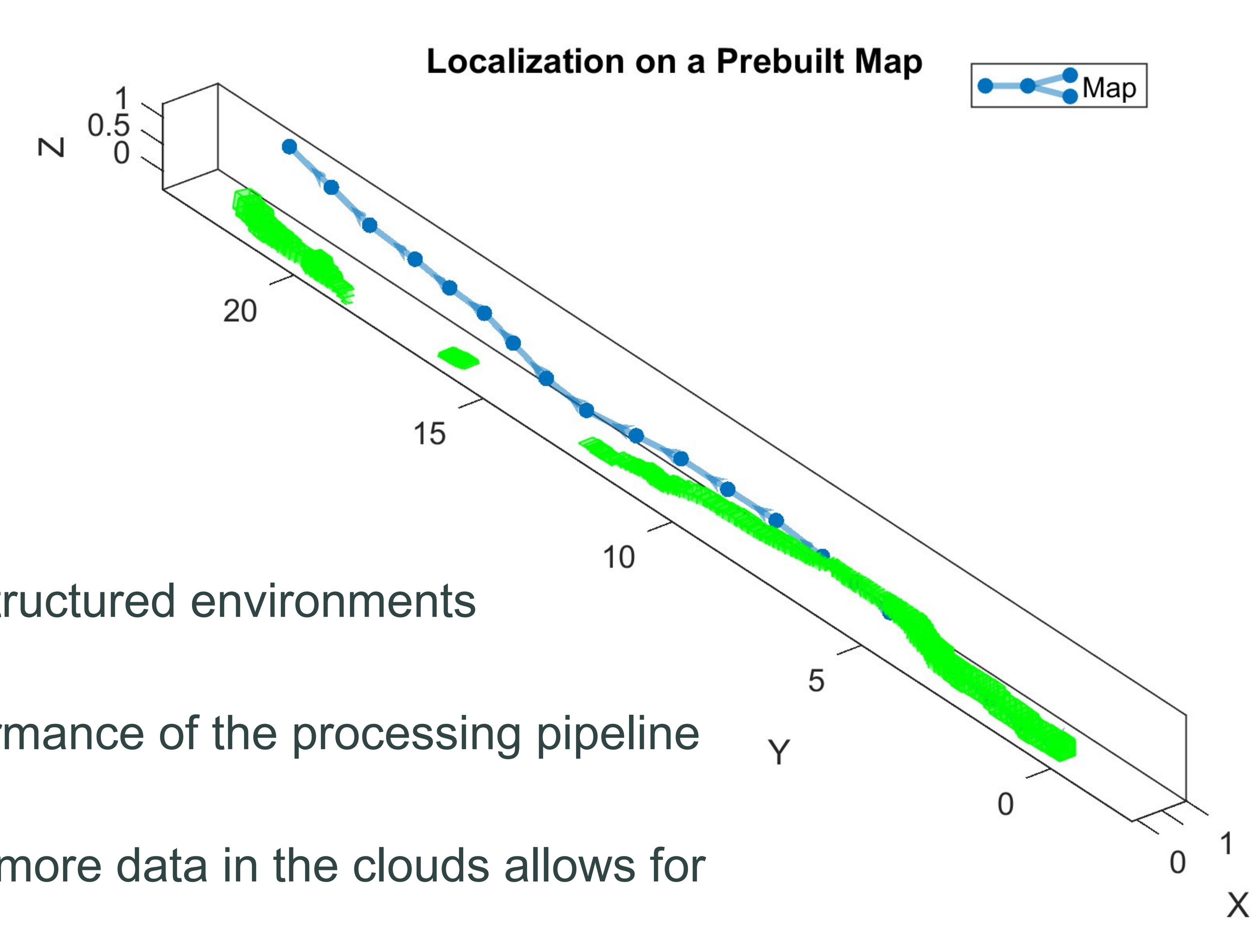
It begins with reading point clouds into the software, pre-processing them and downsampling them. It follows on to the clustering and segmentation using Euclidean distance-based algorithms and completes Eigenvalue-based feature extraction [2][3].

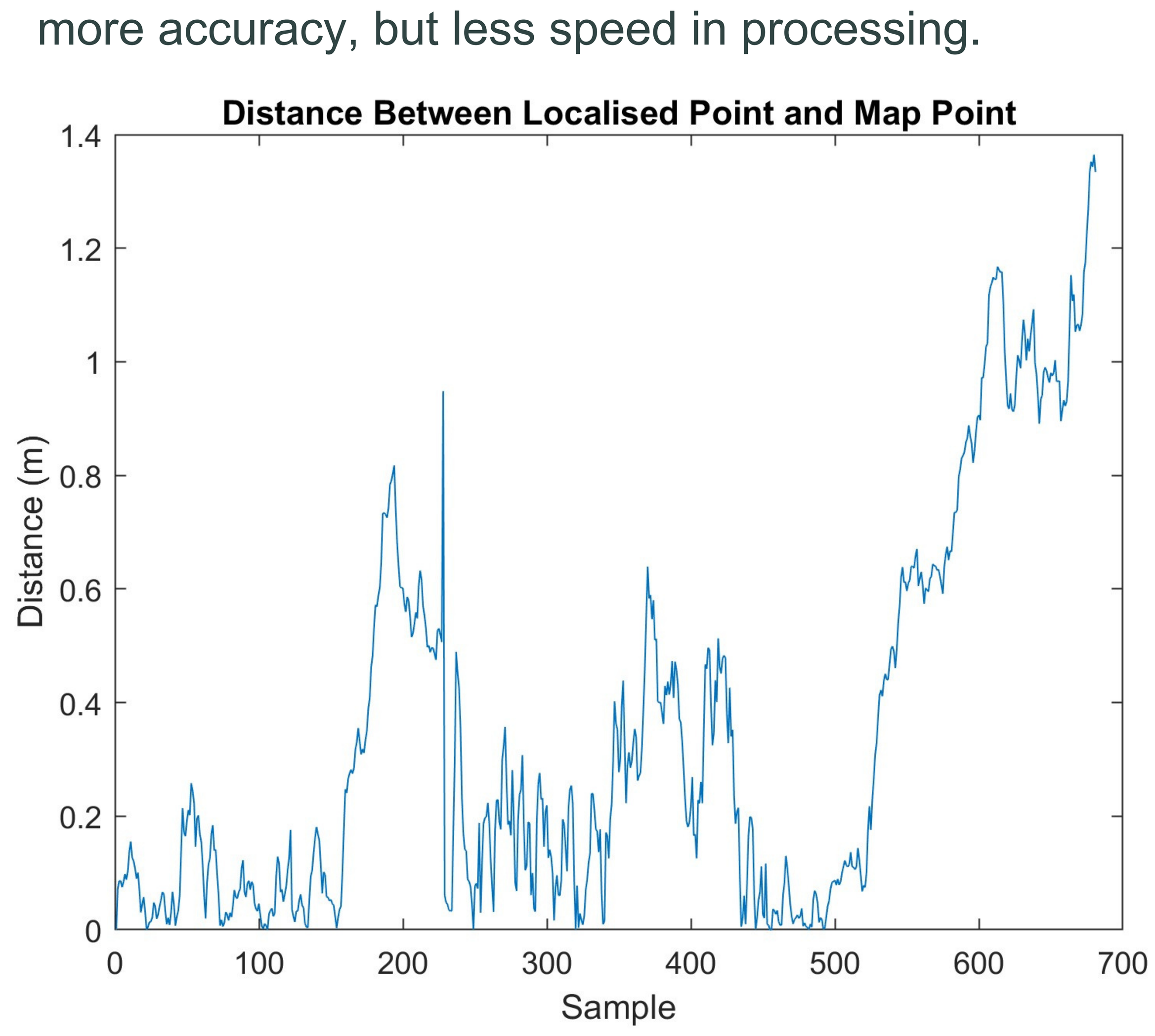
The process builds a map by matching features from segments from consecutive clustered scans, and adding unique segments to a view set.

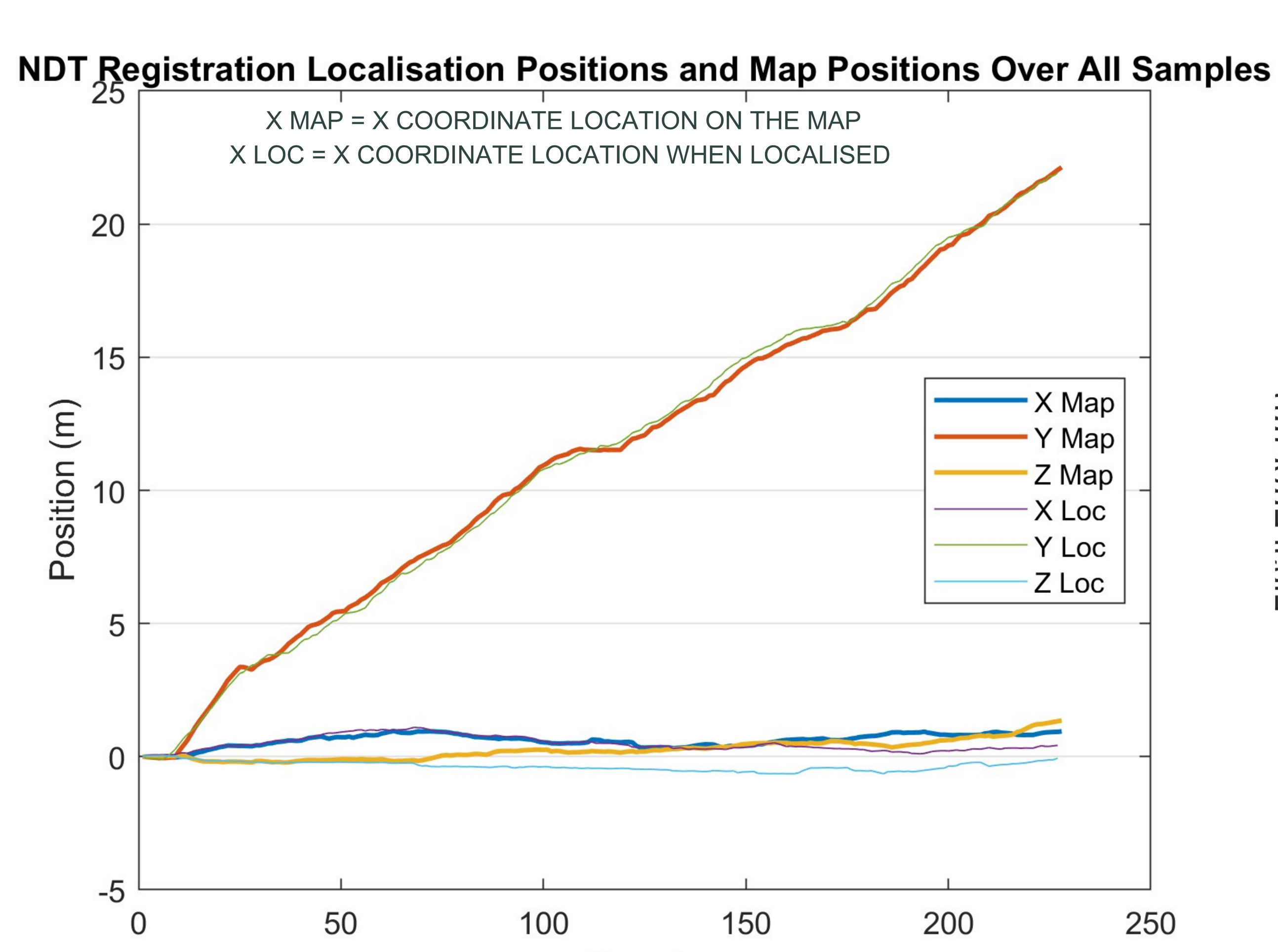
The process can then use scans for localisation, where it matches features and segments from the localisation set, to ones stored in the map (SegMatch), additionally, it uses a Normal Distribution Transform (NDT) Registration method to localise and compare to the map. The outcomes of the map building and localisation are analysed.

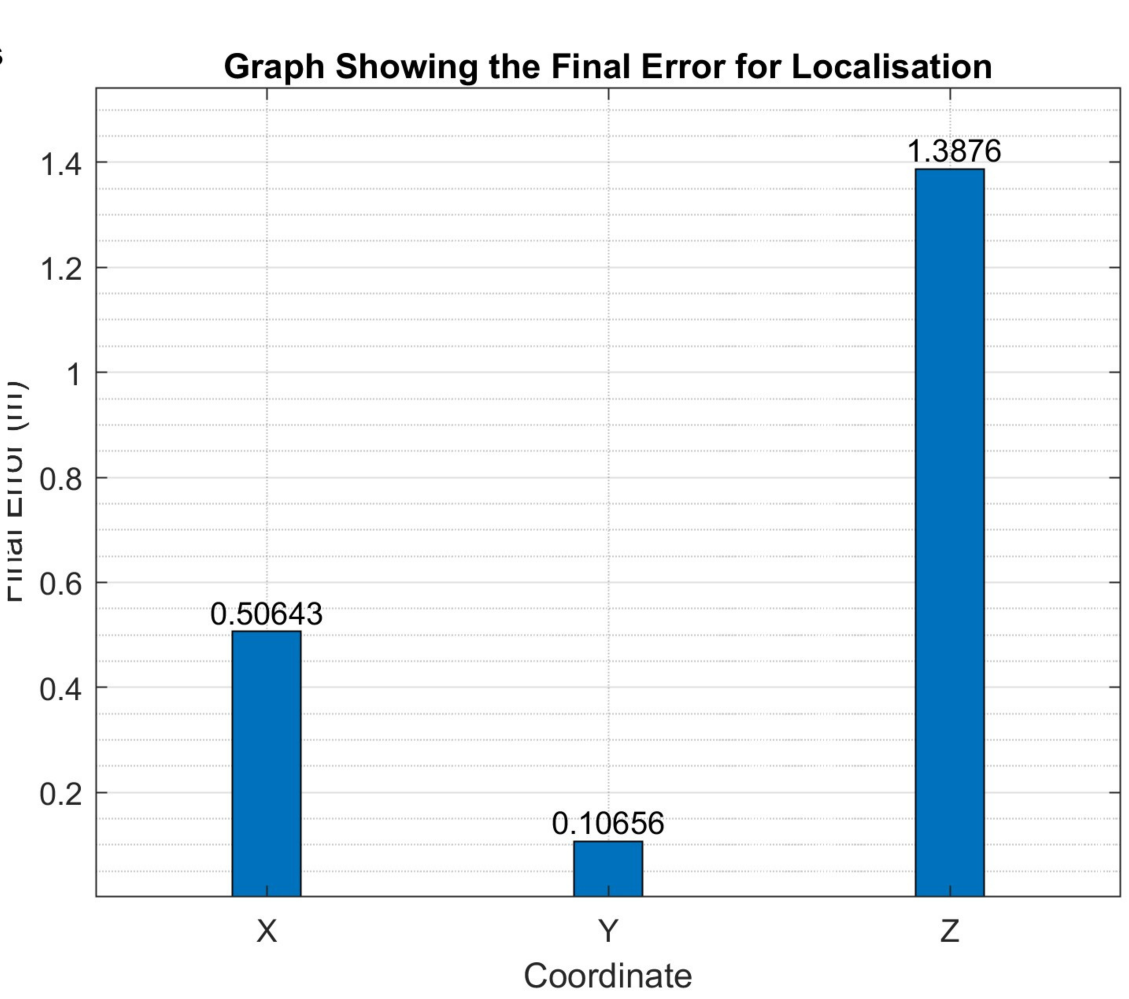
RESULTS & ANALYSIS

- SegMatch was effective for map building but consistently failed to localise a position from the localisation set to a point on the map. This is because upon investigating the feature matching process, for the given data, the features can only find matches for point clouds within 4 indices from each other in the full dataset.
- For the full clouds, the NDT registration is wholly successful when localising against a map built with SegMatch methods, but accumulates the majority of its small error in the Z dimension. This accumulation of error is suggested to be due to unreliable feature matching, or alternatively, error with the chosen elevation threshold when removing the ground points in the pre-processing stage.
- The structured data used in a comparative study of the processing pipeline's performance in unstructured vs structured environments was run through the pipeline, with negative results.
- Investigations lead to the discovery of the structured data being corrupted, and so further assessment of performance of the processing pipeline in structured environments was impossible.
- There is a trade-off between speed and accuracy when considering cropping clouds to a region or interest, as more data in the clouds allows for more accuracy, but less speed in processing.









CONCLUSION

SegMatch, the key algorithmic component for the processing sequence, proved effective in map building but completely failed at localisation. This was due to the feature matching discrepancy, which when evaluated, showed that if point clouds were too far apart, the feature matching was rendered ineffective. NDT-based registration for localisation was completely effective, however, included a cumulative drift error in the Z dimension. Therefore, with a combination of SegMatch map building, and NDT registration for localisation, the project achieved the goals of localising the Husky on a pre-built map, but future work can investigate more efficient and accurate ways of doing so, and test with improved structured data.

RELATED LITERATURE

[1]
Dube, R., Dugas, D., Stumm, E., Nieto, J., Siegwart, R., & Cadena, C. (2017). SegMatch: Segment based place recognition in 3D point clouds. 2017 IEEE International Conference on Robotics and Automation (ICRA), 5266–5272. https://doi.org/10.1109/ICRA.2017.7989618

[2]
Tinchev, G., Nobili, S., & Fallon, M. (2018). Seeing the Wood for the Trees: Reliable Localization in Urban and Natural Environments. 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 8239–8246. https://doi.org/10.1109/IROS.2018.8594042

[3]
Tinchev, G., Penate-Sanchez, A., & Fallon, M. (2019). Learning to See the Wood for the Trees: Deep Laser Localization in Urban and Natural Environments on a CPU. IEEE Robotics and Automation Letters, 4(2), 1327–1334. https://doi.org/10.1109/LRA.2019.2895264