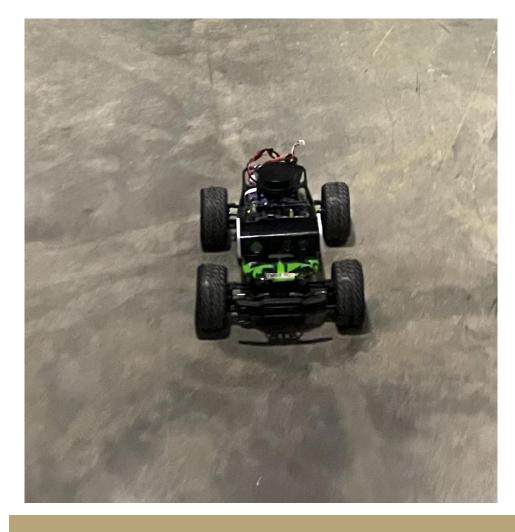


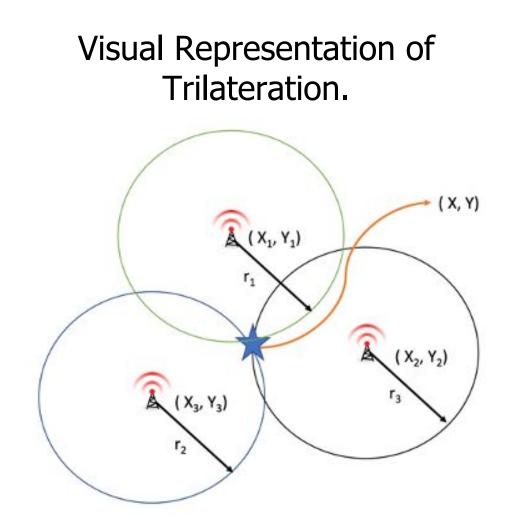
INDOOR LOCALIZATION METHODOLOGIES

- Comparison of Methods of indoor localization using WiFi & LoRa Received Signal Strength Indication (RSSI)
- Two Machine learning based Methods:
- Random Forest Regression
- Long Short-Term Memory (LSTM)
- One Classical Localization Method: Trilateration

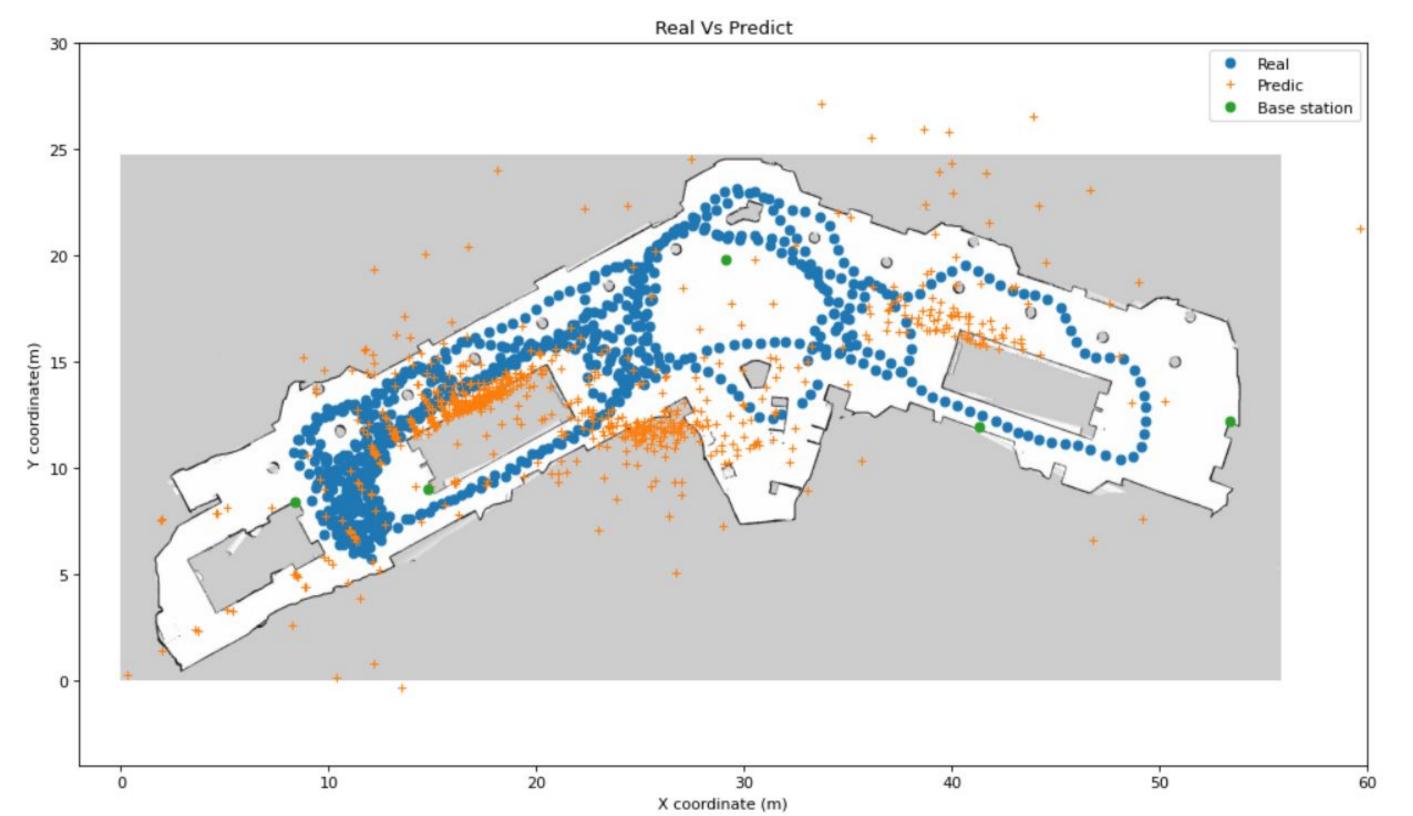


- The ML methods used "Finger Printing" of a Radio Map created by the RSSI values from 89 WiFi access points at known Locations throughout the ECE basement An automated data collection robot was built on a MUSHR car platform to collect radio map
- The Trilateration method used LoRa hotspots at known locations in the ECE basement and calculated distance based on Wave Propagation Equations

LOCALIZATION WITH TRILATERATION



- A major advantage of the trilateration technique is its ease of setup and use, as it does not require training data or a "database"
- Trilateration is not as computationally intensive as some other techniques.
- Information about antenna gain and path loss is required for accurate position estimation
- Trilateration is subject to multipath errors



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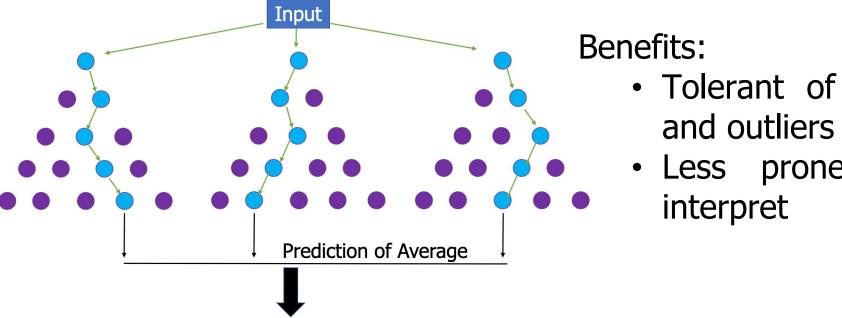
UNIVERSITY of WASHINGTON

EVALUATION OF INDOOR LOCALIZATION METHODOLOGIES: A COMPARATIVE STUDY OF TRILATERATION, LSTM, AND RANDOM FOREST REGRESSION

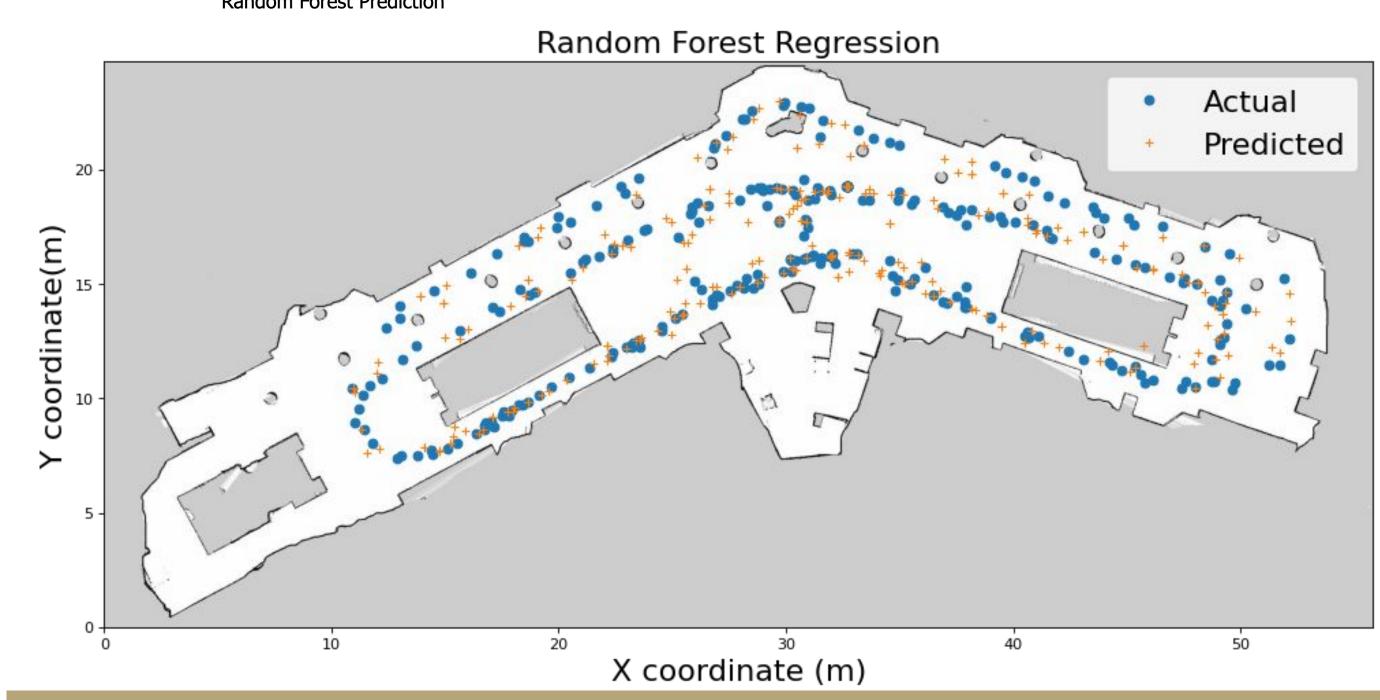
STUDENTS: JOAQUIN SANTECCHIA, KAI LUO, ALEX SKLAR, & RODRIGUEZ PHAM

LOCALIZATION WITH RANDOM FOREST REGRESSION

Random Forest is a machine learning method that constructs multiple decision trees on randomly selected data subsets to improve prediction accuracy while reducing overfitting, requiring a large dataset and computational resources for training.

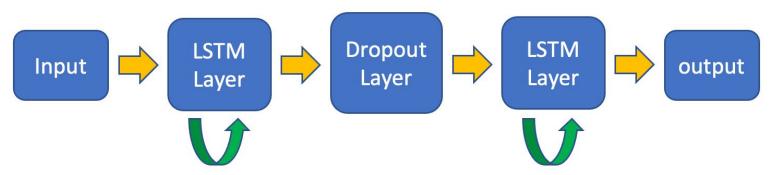


Random Forest Prediction

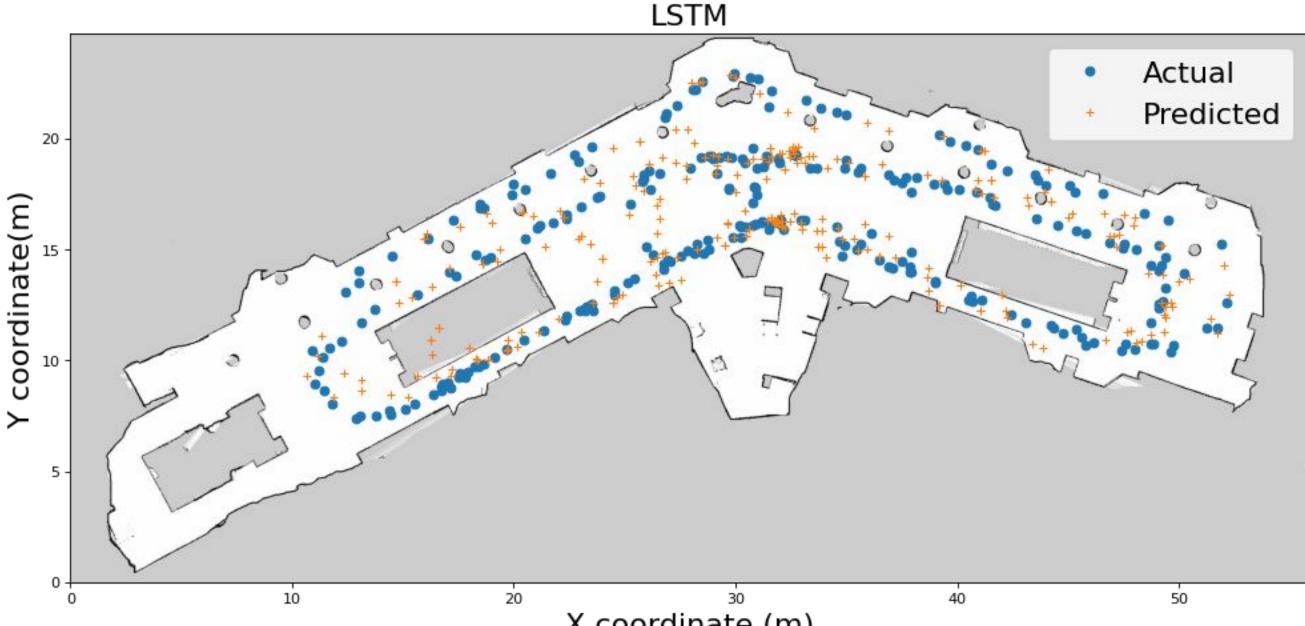


LOCALIZATION WITH LSTM

Long Short-Term Memory (LSTM) is a machine learning method that is well-suited for modeling long-term dependencies in time series data.



For this research methodology, the proposed model features two LSTM layers after the input layer and employs a single drop-out layer in between the two LSTM layers to prevent overfitting. This structure was chosen for its simplicity and ease of implementation.



X coordinate (m)

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• Tolerant of missing data, multiple features, • Less prone to overfitting and easier to



Average Euclidean Error (meters) and Mean Squared Error (MSE) to evaluate the accuracy performance of the models utilized.

- known as well as hardware characteristics for path loss calculation.
- less memory

Random Forest Regression proved to be the most effective method of the three. Our future work will evaluate real-time performance on an embedded system and explore sensor fusion methods to improve accuracy. Random Forest Regression shows the most promise for future development based on its performance and computational cost.

ACKNOWLEDGMENT & REFERENCE

Acknowledgments: We would like to express our gratitude to our text reviewer, Anthony Chae, and the advisors, professors, and staff of the Professional Masters Program in Electrical Engineering at the Department of Electrical and Computer Engineering, University of Washington - USA. Furthermore, we extend our heartfelt gratitude to our spouses, partners, and families for their unwavering support and encouragement throughout this journey. Without their support, this work would not have been possible.

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COMPARING LOCALIZATION RESULTS

• The ML-based methods outperformed the trilateration method. Random Forest Regression proved to have the smallest MSE (1.6 m) and Average Euclidean Error (1.1 m).

• The disadvantage of the ML-based methods (Random Forest Regression and LSTM), is the user needs to collect Wi-Fi RSSI data in the environment and train the ML model

• The disadvantage of Trilateration is that the absolute location of the routers needs to be

• Random Forest Regression was quicker to train than LSTM and the learned model consumed

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