

# Lego Robot Guided by Wi-Fi Devices

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# 1. Introduction



Figure 1. The client-server architecture.

Indoor localization is a technique used to determine an object's location by using the Wi-Fi network. The system learns the location information at the offline phase and applies that prior knowledge at the online phase, which is the time the user wants to locate the object's location.

In this project, we will implement an indoor localization function for a movable Lego robot. On top of the localization function, a self-guiding function and auto data collection function will be implemented.

## Lego Mindstorms NXT Robot

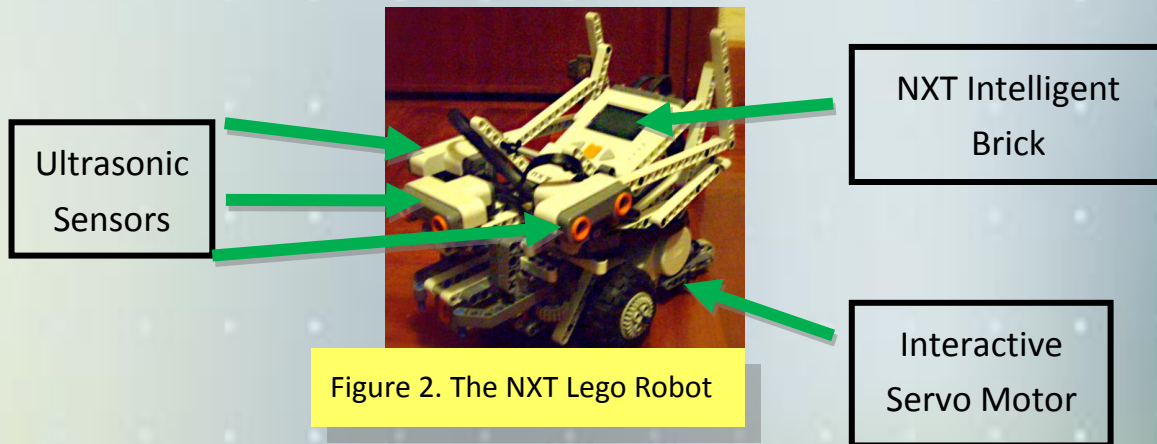


Figure 2. The NXT Lego Robot

## 2. Objective

- Indoor Wi-Fi localization function that is based on analyzing the Wi-Fi signal strength (RSSI) to determine the robot's location
- Self-Guiding function that guides the robot from one location to another.
- Auto Data Collection function that collect Wi-Fi signal strength data automatically.

# 3. Methodology - Localization

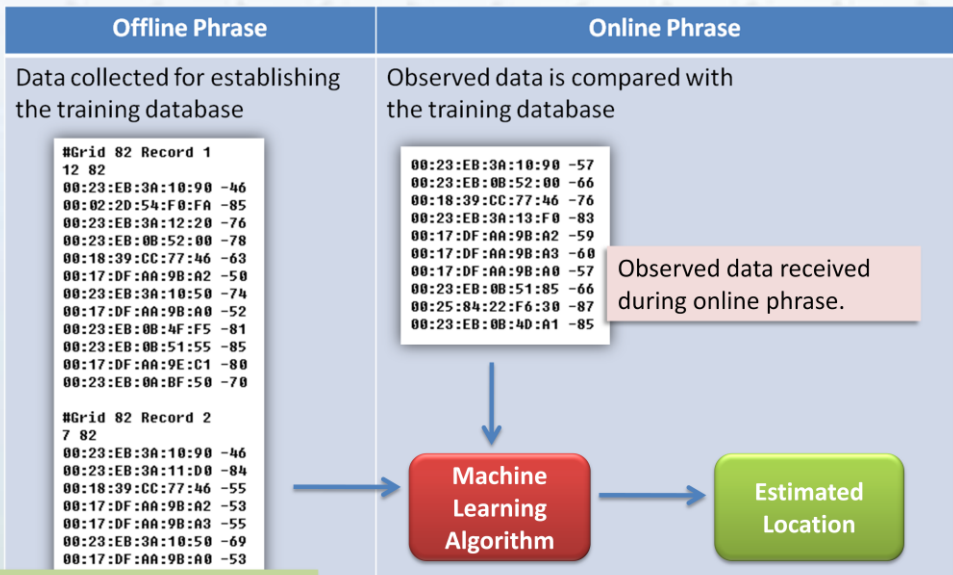


Figure 3. The two phrases for machine learning.

The localization works by using a machine learning approach. In order to make the algorithm works, we have to undergo two phrases : offline and online phrase.

The training database (location knowledge) and the observed signal data are passed to the machine learning algorithm for location estimation.

## Machine Learning :

### Bayesian Probability

Bayesian approach is based on signal strength distribution of access points on each grid cell.

- mitigates the random errors
- adopts probability measurements

## Bayesian Formula

$$\begin{aligned}
 &< o_1, o_2 \dots o_i > : \text{observed data} \\
 &o_i : \text{rss value of observed data} \\
 &s_i : \text{rss value in database} \\
 &= P(\text{Grid} = k \mid \langle o_1, o_2 \dots o_i \rangle) \\
 &= \frac{P(\langle o_1, o_2 \dots o_i \rangle \mid \text{Grid} = k) * P(\text{Grid} = k)}{P(\langle o_1, o_2 \dots o_i \rangle)} \\
 &= P(\langle o_1, o_2 \dots o_i \rangle \mid \text{Grid} = k) * \text{constant} \\
 &= P(o_1 = s_1 \mid \text{Grid} = k) \\
 &\quad * P(o_2 = s_2 \mid \text{Grid} = k) \dots P(o_i = s_i \mid \text{Grid} = k) \\
 &= P(o_1 = s_1) * P(o_2 = s_2) \dots P(o_i = s_i)
 \end{aligned}$$

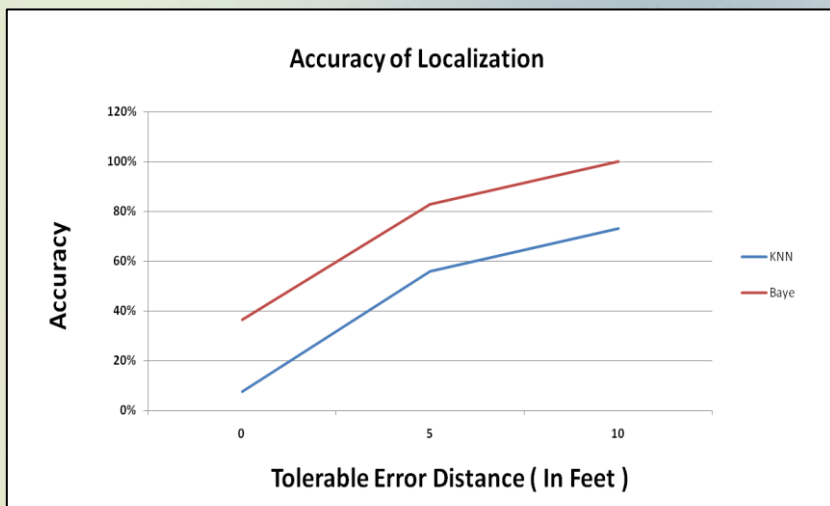


Figure 4. A graph showing the accuracy of the localization function.

## Result

The testing results reveal that the localization using Bayesian probability approach has accuracy above 80% (within 5 feet) and is generally higher than other popular machine learning algorithm such as K-Nearest Neighbor (KNN).

# Methodology- Self-Guiding

The self-guiding function guides the robot from one location to another inside our predefined grid map.

The inputs required for the self-guiding function are the starting location and the destination. The self-guiding function will generate the shortest path between these two points based on Breadth First Search (BFS).

During the robot's journey, if it detects any obstacles or deflection due to mechanical errors, the function will try to bypass and correct them. In case of a total blockage, the function will try to generate an alternate path that guides the robot to the destination.

## 4. Conclusion

We have successfully developed **three major functions** that compensate each other.



The localization function helps the self-guiding function to guide the robot. The self-guiding function guides the robot around for data collection. The auto data collection function collects new signal strength data for future location estimation.

## 5. Areas for Future Research

- Transfer Learning (Time, Devices)
- Reducing effort in collecting training database
- Multiple robots connections

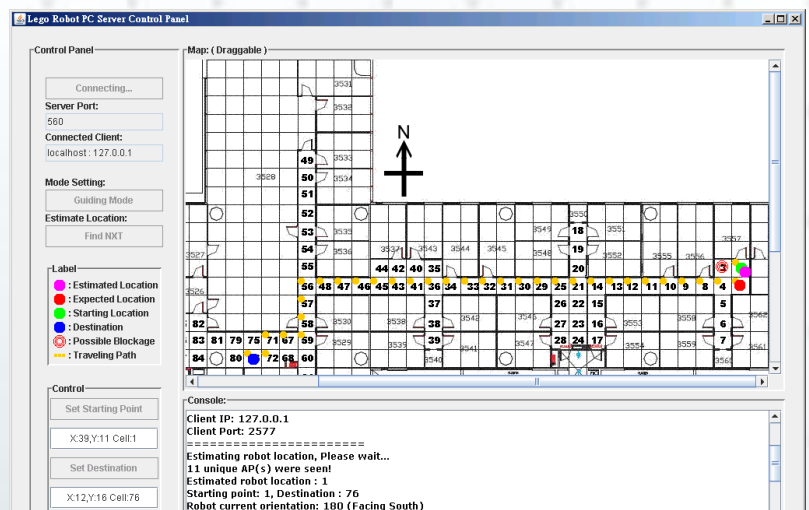


Figure 5. A screenshot of the self-guiding function on the GUI.