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# Multimodal Localization for Autonomous Agents

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## Abstract

*Inventory management and handling in warehouse environments have transformed large retail fulfillment centers. Often hundreds of autonomous agents scurry about fetching and delivering products to fulfill customer orders. Repetitive movements such as these are ideal for a robotic platform to perform. One of the major hurdles for an autonomous system in a warehouse is accurate robot localization in a dynamic industrial environment. Previous LiDAR-based localization schemes such as adaptive Monte Carlo localization (AMCL) are effective in indoor environments and can be initialized in new environments with relative ease. However, AMCL can be influenced negatively by accumulated odometry drift, and is also reliant primarily on a single modality for scene understanding which limits the localization performance. We propose a robust localization system which combines multiple sensor sources and deep neural networks for accurate real-time localization in warehouses. Our system employs a novel deep neural network architecture consisting of multiple heterogeneous deep neural networks. The overall architecture employs a single multi-stream framework to aggregate the sensor information into a final robot location probability distribution. Ideally, the integration of multiple sensors will produce a robust system even when one sensor fails to produce reliable scene information.*

## Introduction

Warehouse material handling robots are transforming fulfillment warehouses, offering unprecedented speed efficiencies and cost reductions. Many of these types of autonomous agents are constrained to fixed paths, both for scheduling ease, as well as limitations in robot localization and object detection. Automated warehouses rely on metallic tracks in the floor or the addition of artificial landmarks in the environment. These tracked or wire-guided systems can be expensive to install. Landmark systems such as visual or QR identification tags inserted at known locations need to be precisely placed. These landmarks can be prone to failure in poor lighting conditions, occlusions, dust, or other debris which impact the ability to recognize landmarks. Such systems typically utilize fixed paths of orthogonal grid lines throughout the warehouse. Although these paths are simple for scheduling algorithms, they do not allow robots to follow shortest path routes and can impart prolonged wait periods if a path is obstructed.

We propose a system which will allow autonomous robots to roam freely in a warehouse, making overall operations more efficient. Accurate robot localization is important for maintaining robust path planning and avoiding static and dynamic obstacles. Using LiDAR and odometry sensor data with statistical inference methods such as particle filters are less robust to dynamic environment changes. These methods have a narrow scope and have less room for improvement in terms of localization accuracy. Deep learning approaches have shown promising results in image retrieval and localization tasks which can be applied to autonomous agents. We introduce several independent deep learning frameworks using multiple data modalities for robust robot localization. In addition to the independent frameworks, a single multi-stream framework was designed to aggregate features from all available modalities.

To provide accurate robot localization which is robust to active warehouse environments, data from multiple sensors with different strengths is used to create a robust *super sensor*. This super sensor accumulates sensor readings from multiple modalities with the goal of producing not only higher confidence localization information, but also emphasizing the strengths of each modality. For example, in low light conditions, a radio-frequency based localization system would be more effective than a vision based system.

A prototype of the robot platform that we are using for experimentation is shown in Figure 1.

***Figure 1.*** *The experimental robot platform used to evaluate the proposed localization techniques. At the top is a Kodak PixPro sp360 4K omnidirectional camera placed on top of a Velodyne VLP-16 3D LiDAR. A TPLink Talon AD7200 60 GHz millimeter wave router is located on the top shelf. A Decawave DW1000 UWB transceiver is mounted on the top shelf visible underneath the VLP-16. An Alienware 15 r4 laptop handles localization inference and navigation.*

## Related Work

Ultra-Wide Bandwidth (UWB), Bluetooth, and Radio Frequency Identification (RFID) beacons are the most widely used technologies for wireless localization in indoor environments [1, 2]. RFID beacons, although accurate and precise, involve costly installation process and costly hardware due to a short detection range of around a few decimeters [1]. In contrast, UWB and Bluetooth beacons are low cost, easy to deploy, and provide a long detection range and omnidirectional coverage [2, 3]. These properties ensure a high degree of coverage in a dynamic warehouse environment. Alarifi et al. [3] provides an extensive comparative analysis of UWB technology for indoor positioning. UWB provides high multipath resolution and better obstacle transmittance as compared to other technologies [3]. Tiemann et al. [4] provides a proof of concept for UWB indoor positioning using a global navigation satellite simulation system.

WiFi based indoor localization has been extensively studied in literature [5, 6]. Recent techniques have used machine learning based approaches. Zhang et al. [7] use a Deep Neural Network (DNN) with Hidden Markov Model (HMM) to further fine tune the location prediction. Lemic et al. [8] evaluate the performance of millimeter-wave wireless systems for localization and have shown that the same techniques that have been used with standard WiFi can be used in millimeter-wave systems. The results were simulation based, and the hardware changes required to generate the necessary signals for different localization techniques were not discussed. Bielsa et al. [9] use off the shelf 60 GHz hardware for a location estimation system using particle filters with linear programming and Fourier analysis to achieve sub meter accuracy. Although accurate, their methodology used 400 measurements per location which could be time consuming for a large scale deployment.

Recent work has shown improved localization accuracy with 60 GHz wireless technology, but most of these works are based on the simulation modeling of the wireless channel and then using trilateration (distance-based) or triangulation (angle-based) localization techniques [8, 10]. These techniques either require correct estimation of the channel model or custom design of wireless sensors. Accurate channel state information in the 60 GHz band is challenging to estimate due to variability caused by shadowing effects in a dynamic environment such as a warehouse. Custom 60 GHz sensors are also expensive and may become prohibitive when necessary for hundreds of autonomous material handling agents. Therefore, mechanisms to estimate location which are more resilient to statistical variation in the channel model such as machine learning techniques can be potentially applicable. Due to these reasons, in our work, we explore localization with consumer-grade Access Points (APs) in the form of 60 GHz wireless routers using machine learning.

## Multimodal Sensors

In this section, we will discuss the sensors that we have used to design our proposed multimodal localization system. Our system consists of vision and Radio Frequency (RF) based sensors. For vision, we utilize an omnidirectional camera oriented towards the ceiling for maximum scene coverage. For the RF based wireless sensors we utilize UWB beacons and 60 GHz wireless routers as millimeter wave (mm-wave) based sensors.

### *Omnidirectional Camera*

The millions of pixels in a camera frame offer feature-rich detailed information about the environment. Natural landmarks such as wire conduits and lights in the ceiling, as well as doorways and variation in aisle layout provide a unique signature for each location. There are also many features that may not be desirable for generating these fingerprints such as temporary obstacles or shelf inventory in a warehouse. It is important to distinguish between the static features relevant to each location in an environment and the dynamic features that may not be present in the future. We utilize an omnidirectional Kodak PixPro sp360 4K camera which provides a wide image of the surrounding environment. The camera is oriented upwards such that each acquired image captures the ceiling above and features all around the platform (see Figure 2.)

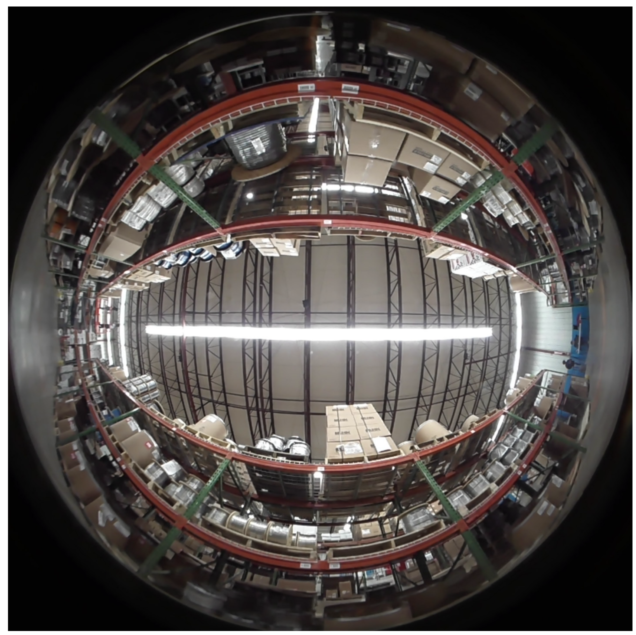

***Figure 2.*** *Omnidirectional camera frame captured by a Kodak PixPro sp360 4K camera inside a warehouse environment.*

### *Ultra-Wideband Sensor*

Radio wave based positioning technology varies widely depending on the environment in which they are deployed. Factors such as density of objects, dynamic movements, surface reflections, and proximity to landmarks can affect performance. UWB indoor localization technology has been proven to give better performance in industrial environments [3]. We chose to use the MDEK10001 UWB Development kit by Decawave as it shows superior performance compared to other commercially available UWB systems [11]. Decawave also provides an open source software stack for developing scalable RTLS solution. Tags are the mobile terminals mounted on the autonomous agent and anchors are the fixed terminals with known location in the environment.

Indoor radio localization systems typically involve two steps: first retrieve the distance values from a tag to at least three anchors whose locations are known, then calculate the $x, y$ coordinate estimate of tag using geometrical algorithms [3]. The first step can use Time Of Flight (TOF), Time Difference Of Arrival

(TDOA), Phase Difference Of Arrival (PDOA), or Received Signal Strength Indicator (RSSI) models. Given these distances, geometrical algorithms for estimating the location coordinates include trilateration, linear least square method, or triangulation. MDEK1001 UWB uses two way-TOF for calculating the distance between a tag and each anchor and then uses trilateration for estimating the location coordinates of the tag. The UWB tag connects and estimates distance to the nearest four anchors using the two way-TOF algorithm. These four distances are fed into both the Decawave trilateration algorithm as well as our Multi-Layer Perceptron (MLP) neural network. Although it might be possible to estimate location from more than the four nearest anchors, the Decawave's RTLS firmware only reports the nearest four anchor distances. Further, a two wavelength based RF indoor localization (mmWave and UWB) can provide a consistent location estimates even in noisy environments.

### 60 GHz Wireless Sensor

There have been many recent advancements in high frequency mm-wave wireless technology that ranges between 30 GHz to 300 GHz. In particular, for the unlicensed 60 GHz spectrum, efforts have been made for design of tri-band wireless APs capable of operating at 2.4 GHz, 5 GHz and 60 GHz. The 60 GHz carrier allows higher data rates of multi-gigabit-per-second making it suitable in many applications that require high speed wireless data rates such as smart cities. The signal propagation at 60 GHz can cause large signal attenuation through concrete materials, hence 60 GHz based localization systems are more suitable for the indoor environments. In our work we have used TPLink Talon AD7200 wireless router as 60 GHz wireless sensor.

Utilizing 60 GHz wireless routers, we capture the Received Signal Strength (RSS) signals at the client from all available APs. We set up the 60 GHz routers in client and the APs mode by using the firmware provided by Bielsa et al. [9]. The RSS signals captured by the client at different locations are used as the input features by the learning model and the different locations at which the features are captured are the corresponding ground truth (GT) labels. For each GT label we will have $1 \times N$ input features, where $N$ is the number of APs. The data collected using the 60 GHz sensors at different GT positions represents a radio map. Where a point in the radio map gives the RSS signal information seen by the client from all available APs.

## Architecture of the Multimodal Localization System

Warehouses have very dynamic environments. For example, the amount of stock on the shelves constantly changes, manually operated forklifts and employees pass by at unpredictable instances, and inventory stockpiles come and go on the warehouse floor. We propose a multimodal localization strategy which emphasizes the strengths of individual modalities, together making a more powerful sensory system.

### Omnidirectional Camera Model

The structure of the omnidirectional camera model is shown in Figure 3. Omnidirectional camera frames are used as input for a 50-layer ResNetv1 [12, 13] deep neural network architecture. Discrete locations in the environment are mapped to individual class assignments from the network. An additional classification head allows for orientation classification. For a single warehouse aisle in the testing environment, there are 438 unique cataloged locations from which the images originate. There are 36 different orientation classes which correspond to increments of 10 degrees of rotation.

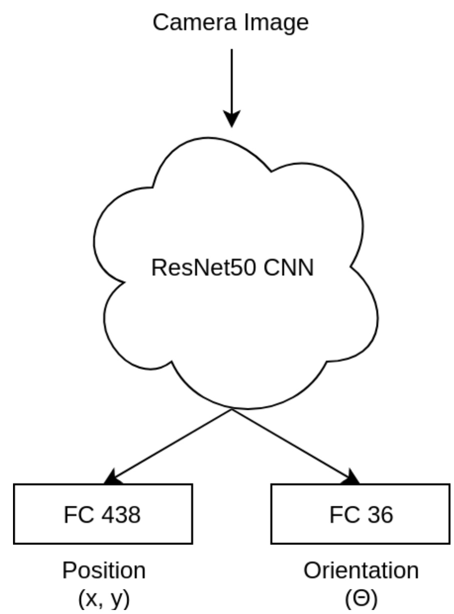


***Figure 3.*** *Omnidirectional camera position and orientation classification network based on a 50-layer ResNetv1 CNN. Two classification heads produce predictions for both position and orientation.*

### UWB Model

The RF based localization exhibits non-linear behavior due to environment density (proximity to walls, variability in stocked shelves) and surface reflections. Linear approaches such as trilateration fail to model these complexities. A MLP neural network was implemented for mapping the tag to anchor distances to tag $x, y$ coordinates. For this research, the MLP inputs consist of 28 tag to anchor distances and output $x, y$ coordinates of the agent in the form of a class label.

Two MLP models were used for RF localization. A three layer MLP classification model shown in Figure 4, and a five layer MLP regression model shown in Figure 5. The classification model had 438 discrete locations using two hidden layers, each with 64 neurons. The regression model reported floating point $x$ and $y$ values and used four hidden layers, each with 64 neurons.

### 60 GHz Model

The collected RSS signal dataset represents a radio map of the environment. Figure 6 shows the MLP based classification model consisting of two hidden layers, each with 64 hidden neurons. The input to the MLP are the RSS signals from the 10 APs and the output layer consists of 438 nodes representing the 438 GT labels.

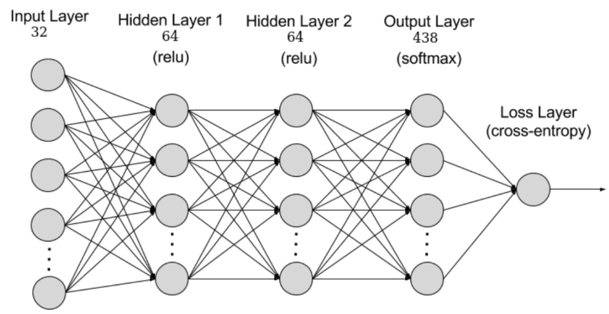


*Figure 4.* *Three layer MLP classification model implemented for UWB sensor.*

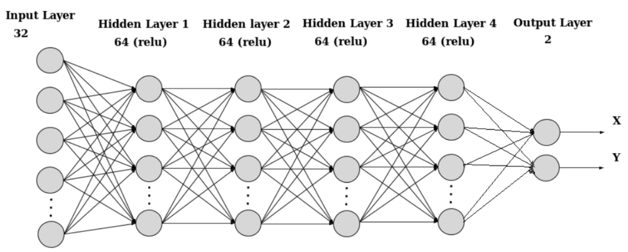


*Figure 5.* *Five layer MLP regression model implemented for UWB sensor.*

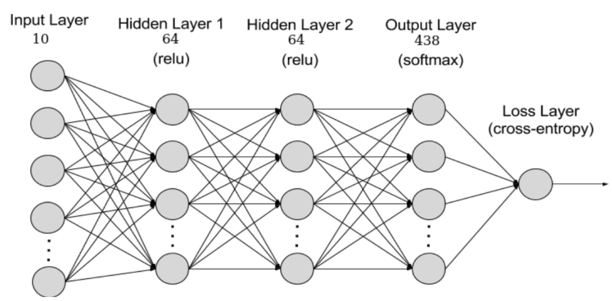


*Figure 6.* *Three layer MLP classification model implemented for 60 GHz wireless sensor.*

## Combined Multimodal Model

Figure 7 shows a single localization model incorporating all of the previous sensor models. This combined *super sensor* model implements three parallel streams: a three-layer MLP for the 60 GHz information, a three-layer MLP for the UWB information, and a 50-layer ResNetv1 for the omnidirectional camera frames. The previously described independent implementations of these networks include one or more classification head layers as the final component of the networks. For the combined implementation, these independent classification heads were removed leaving only the feature vectors extracted from the raw sensor data. These feature vectors were then concatenated together and passed into a final position classification head. This allows the final position classification layer to draw features from all available sensors simultaneously.

## Data Collection and Experimental Setup

The robot platform used for experimentation (see Figure 1) is based on a differential-drive RoboSavvy Self-balancing Platform with two swivel caster wheels for passive platform stability. An Alienware 15 R4 laptop with an Intel i7 8750H, 32GB of DDR4 memory, and an NVIDIA GTX 1060 runs Ubuntu 16.04 with Robot Operating System (ROS) Kinetic to handle navigation and communication. A Velodyne VLP-16 3D LiDAR and a Kodak PixPro sp360 4K omnidirectional camera are positioned at the top of the robot platform for maximum scene coverage. Two radio frequency based ranging sensors are used, a Decawave DW1000 UWB transceiver and a TPLink Talon AD7200 60 GHz millimeter wave router. UWB transceivers calculate distance from TOF using a Two Way Ranging (TWR) algorithm. 60 GHz wireless routers are used to generate a radio map by feeding the received signal strengths into an MLP.

The scope of this research includes an area of approximately 2.74 meters (9 feet) by 20.11 meters (66 feet) encompassing a single aisle inside an operating warehouse (see Figure 8). The aisle was divided into multiple coordinate locations, where a mesh grid intersection within the aisle represents the location at which we collect the GT signals for model training. Each of the locations are carefully marked in a grid pattern using measuring tape and lasers for precise alignment. The separation between the marked locations along the horizontal axis (x-axis) is 0.3048 meters (1 foot) and in the vertical axis (y-axis) is 1.8288 meters (6 feet). From the edge of the aisle we have kept the separation of 0.6096 meters (2 feet). An additional 1.8288 meters past the end of the aisle was also marked and recorded for experimentation. The total coverage with the included extension is 1.8288 meters (6 feet) by 21.95 meters (72 feet.)

The topology of the space used for experimentation is shown in Figure 9. We configured a 60 GHz router in a client mode using the firmware provided by Bielsa et al. [9]. The client then runs our in-house scripts that continuously scan for APs and records the

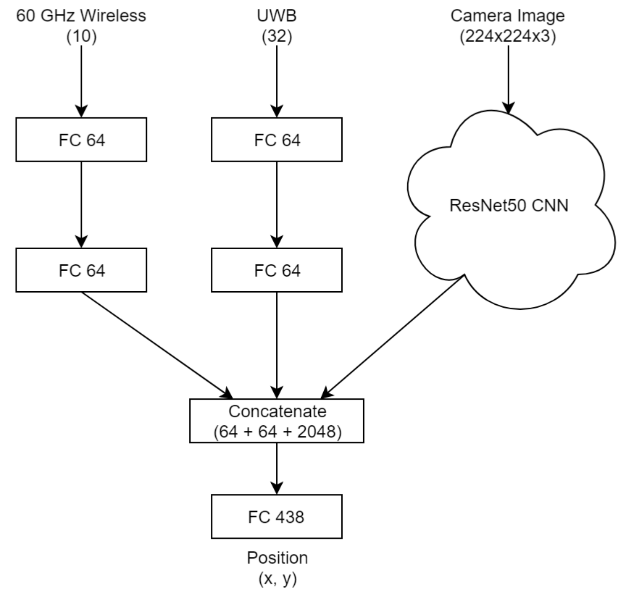


*Figure 7.* *Multimodal position classification network. Two MLP networks operate on the 60 GHz RSS and UWB distance values. A 50-layer ResNetv1 CNN generates features from the omnidirectional camera frame. All features are concatenated into a single vector and passed into a final position classification head.*

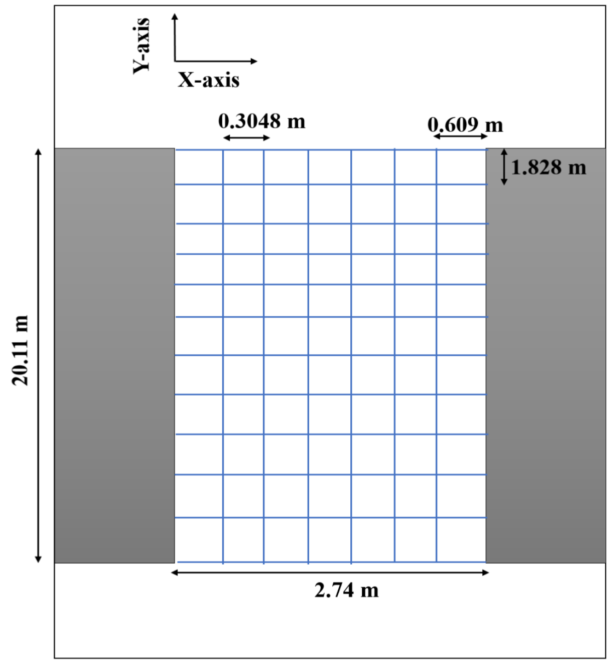


*Figure 8. Coordinate layout of localization evaluation environment. Six horizontally spanning intersection points are positioned 0.3048 meters apart. The vertically spanning intersection points are spaced 1.828 meters apart. An additional buffer region is placed between the recorded coordinates and the aisle shelves.*

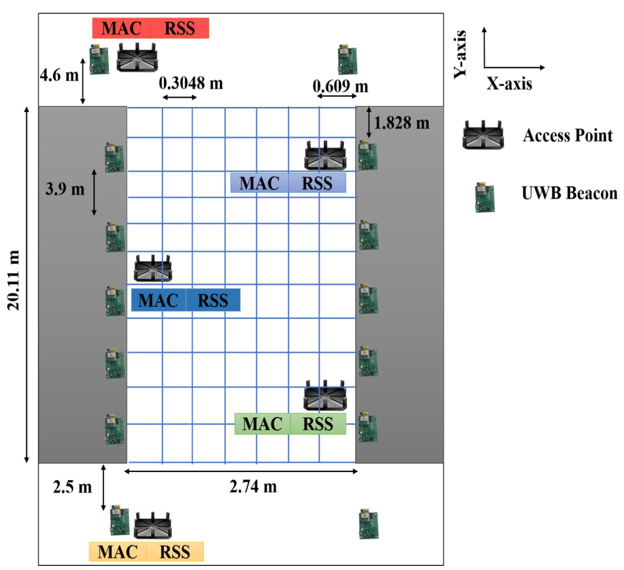


*Figure 9. UWB and 60 GHz wireless sensor topology for a single warehouse aisle.*

RSS signals along with the MAC address. The APs are mounted on the warehouse ceiling along the aisle in a zig-zag arrangement. This arrangement is used to maximize the coverage of the RSS signals received by the client. The routers on the ceiling are configured in AP mode. Inside the warehouse we have mounted ten APs on the ceiling with five APs per aisle. In our analysis, we have collected the data in one of the aisles and performed localization in that particular aisle only.

For UWB, 28 DWM1001 DEV modules were installed on the ceiling of the warehouse. The anchors were installed in two aisles of the warehouse to achieve a more consistent Line Of Sight (LOS) between UWB modules at all locations and aisle end caps. A DWM1001 DEV module (in tag mode) is installed on the robot. The four best anchors within its proximity are selected at regular intervals as the robot moves around.

A total of 10 complete position datasets were collected with the omnidirectional camera and 60 GHz RSS values. Seven of these runs contained UWB distance range values.

## Experimental Analysis

Two different approaches were investigated: independent sensor models and a single multimodal sensor model. For each of the models, two of the available position datasets were held out during training for evaluation. One of the held out evaluation datasets was captured with an offset of about eight centimeters purposely introduced to evaluate the ability for each of the models to generalize well. A summary of the localization performance results is shown in Table 1.

**Table I: Localization performance results for each of the proposed localization networks. Accuracy is determined from correct classification of test data labels.**

| Sensor | Training Sets | Position Accuracy | Orientation Accuracy |
|---|---|---|---|
| Camera | 8 | 92.63% | 99.99% |
| UWB | 5 | 59.00% | N/A |
| 60 GHz | 8 | 24.67% | N/A |
| Combined | 8 | 90.71% | N/A |

The omnidirectional camera model was trained utilizing eight of the available warehouse aisle datasets and evaluated using the two held out datasets. The accuracy for the held out datasets converged to 92.63% for position classification. An orientation classification accuracy of 99.99% was quickly achieved for the omnidirectional camera model as shown in Figure 10. After 22,000 training iterations the orientation classifier head was able to achieve an accuracy upwards of 99.9% on the held out evaluation datasets. The position classification head evaluation accuracy converged to 92.2% after training 180,000 iterations. These results validate the ability to accurately localize within the warehouse environment utilizing omnidirectional image features.

The MLP classification model for the UWB sensor was trained on five datasets and evaluated on the two held out datasets. The classification model produced an accuracy of 59% on the test dataset. We use Root Mean Square Error (RMSE) as a metric to measure the performance of the MLP regression model. The MLP regression model has a RMSE of 0.21 meters while the RMSE with trilateration is 1.415 meters. This demonstrates improved performance with the MLP regression model over the standard trilateration approach The experimental results also showed the MLP based approaches perform better in situations when there is lack of line of sight from tag to anchor in comparison to the trilateration approach alone.

The implemented MLP for the 60 GHz sensor is trained on eight datasets and evaluated on the two held out datasets. The MLP classification model gives an accuracy of 24.67% on the test

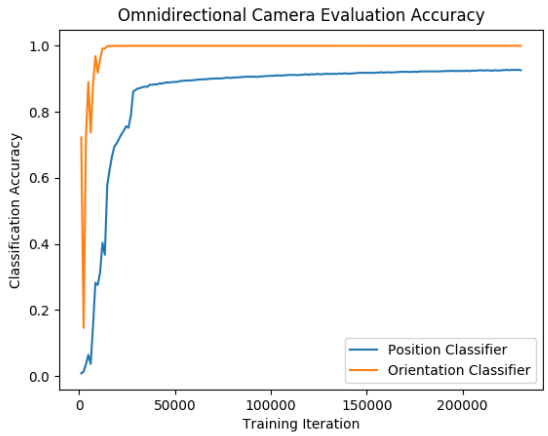


***Figure 10.*** *Evaluation set accuracy for omnidirectional camera localization model.*

dataset. The low accuracy of the MLP can be explained due to the similar or same RSS signal values from the APs at multiple adjacent positions. This similarity of the RSS features is mainly due to the beamforming technique used by the wireless routers, during which the APs and the client tries to maintain the RSS between them to enable better communication coverage.

The combined sensor model consisting of two independent MLP networks for both radio frequency based sensors and a ResNetv1 CNN was trained utilizing all available training datasets with valid readings for all three sensors. The evaluation datasets were consistent with the evaluation sets for the individual sensor architectures. An evaluation accuracy of 90.71% was achieved on the held out datasets.

## Conclusion

Several different localization network topologies were designed and evaluated for different sensors in the scope of this work. The individual omnidirectional camera localization model performed well for determining both the position and the orientation of the agent within the warehouse aisle. The UWB regression localization model demonstrated the ability of a machine learning model to improve upon the standard trilateration localization approach. The usage of 60 GHz for agent localization is in its infancy, but specialized RSS protocols which can improve performance are currently under investigation. The combined multimodal super sensor was challenged as the omnidirectional camera was in isolation much greater than the other modalities.

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