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AUTOMATIC DETECTION OF ACCESS POINT LOCATION USING MACHINE LEARNING AND PRIOR MODEL CALIBRATION

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ABSTRACT

Knowledge of the correct location of an access point (AP) is of vital importance within a wireless ecosystem. Techniques are presented herein that support a new AP location identification method that uses prior model calibrations and machine learning (ML) techniques to detect an AP's location using either received signal strength indicator (RSSI) data or fine time measurement (FTM) protocol data. Among other things, the new method is faster and more accurate than conventional trilateration methods.

DETAILED DESCRIPTION

The correct location of an access point (AP) is of critical importance to a wireless coverage map and for client location services within, for example, a cloud-based location services platform. To provide a sense of the involved scale, a network equipment vendor's customer may have millions of APs in their network and such a customer may employ a vendor's advanced digital network architecture manager to manage many millions of APs.

Currently, to manage their APs a customer must manually enter the positions of those APs in a floor map, a process that is time consuming and prone to error. Customers also frequently move an AP to a new position without updating their advanced digital network architecture manager. Such inaccurate AP position information results in an incorrect wireless coverage map and an erroneous client location in the customer's cloud-based location services platform and their connected mobile experience facilities.

The ability to automatically detect the location of an AP would solve the above-described challenges and, consequently, address many different needs including the detection of, and the issuance of a warning to a user regarding, the moving of an AP to a new location; the development of an estimate of the new location to which an AP has been moved; the detection of the location of a new AP (that is, for example, added to a floor); the determination of whether an AP was incorrectly placed in a floor map; and the self-identification of an AP's location under Wi-Fi 6E.

Techniques are presented herein that support the automatic discovery of the location of an AP, based on the known positions of a small subset of APs, thus addressing the above-described challenges and needs.

The presented techniques support an iterative method for automatically detecting the locations of the APs within the floor of a building or within an outdoor area. That method leverages an estimated distance between APs (such as may be obtained through, for example, a received signal strength indicator (RSSI) derivation); the known location of at least three anchor APs (that may be obtained through any method including a Gypsum module, manual input, or other means); and, optionally, the locations and the geometry of any obstacles such as walls (if such information is known).

As indicated above, the presented techniques may incorporate RSSI-based data. The main challenge associated with using RSSI signal strengths to estimate a distance (and subsequently identify a location) is that radio signal strengths are affected by many unknown factors (including obstacle attenuation, multiple paths, transmission power, antenna orientation and gain variations, etc.), thus resulting in a high level of error (possibly on the order of seven to ten meters (m) or higher).

To address the above-described RSSI-related challenges, the presented techniques employ statistical analysis methods to calibrate RSSI data and, consequently, reduce any errors in a distance calculation; use machine learning (ML) techniques to determine an AP's location from RSSI distances (through, for example, a trilateration method); and, as a result, yield greater accuracy than just gradient descent and Gauss-Newton methods.

The new iterative method that was introduced above utilizes a computationally efficient process involving prior model calibrations and gradient descent or ML techniques to locate the position of an AP more accurately than conventional trilateration methods. The new method is based in part on the standard path loss model that is given by the following formula:

$$RSSI_{ij} = e + K_i + E_j - 2 * \log L_{ij}$$

(or, equivalently, by the formula $M_{ij} = e * K_i * E_j / L_{ij}^2$) where $RSSI_{ij}$ is the signal strength between the APs i and j expressed in decibel-milliwatts (dBm); M_{ij} is the signal strength between the APs i and j expressed in volts; e is a dielectric constant; K_i is the transmission gain of AP i; E_j is the receiving gain of AP j; and L_{ij} is the distance between APs i and j.

According to the presented techniques, several different implementation approaches are possible. Each of those approaches may encompass an iterative process where the inaccuracy of a measurement between known APs may be used as a seed to find a pairwise inaccuracy coefficient that may then be used to test the possible locations of unknown APs. Such a process may be repeated, iteratively, to first find the locations of APs whose positions are coherent with a surface coefficient and then use the newfound AP positions as additional seeds to recursively find the positions of other APs.

A first implementation approach encompasses the use of RSSI data, as described above. Under that approach, the above-described process may be expressed through the nine steps that are presented in Table 1, below.

Table 1: Iterative Process

Step	Activity
1	The values of e_{ij} [a squared matrix] are set to one (1) and the value of E_j is set to 1.
2	The location of each anchor AP is set.
3	The location of each of the unknown APs is set to some estimated location – e.g., a best guess or some random value if unknown.
4	The known or estimated AP locations are used to calculate their estimated distances L_{ij}.
5	A model calibration is completed, where an estimated sender gain K_i is calculated as $(M_{ij} * L_{ij}^2 / e_{ij} * E_j)$.
6	A model calibration is completed, where an estimated receiver gain E_j is calculated as $(M_{ij} * L_{ij}^2 / e_{ij} * K_i)$.
7	A model calibration is completed, where an estimated dielectric gain e_{ij} is calculated as $(M_{ij} * L_{ij}^2 / E_j * K_i)$.
8	Under a forward model, an AP-to-AP range R_{ij} is calculated as sqrt $(e_{ij} * K_i * E_j * \text{constant} / M_{ij})$.
9	Under an inverse model, given R_{ij} from step 7 (above) trilateration or ML techniques are used to find AP locations that minimize the range error $\|\| R_{ij} - L_{ij} \|\|$.
10	The new AP locations are used to recalibrate the model and steps 4 - 10 (as described above) are repeated until any range errors converge to a minimum.

Multiple tests have shown that the above-described process very quickly converges to an optimal solution when compared to conventional model inversion which is often unstable when there are many prior model parameters such as (e.g., wall, etc.) obstacles.

Additionally, compared to a closed-form trilateration method the above-described iterative process yields much more accurate location estimations. To illustrate the accuracy that is possible under the first implementation approach, consider the exemplary floorplan (containing a number of APs) that is presented in Figure 1, below:

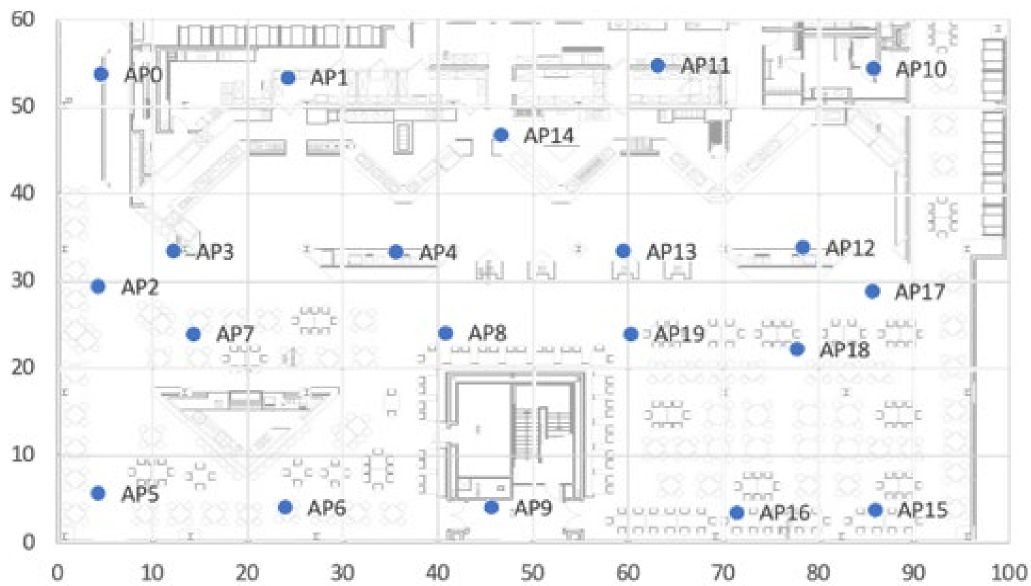

Figure 1: First Implementation Approach – Exemplary Floorplan

Based on the above exemplary floorplan, the average error of 12m that arises from a conventional trilateration approach is depicted in Figure 2A, below:

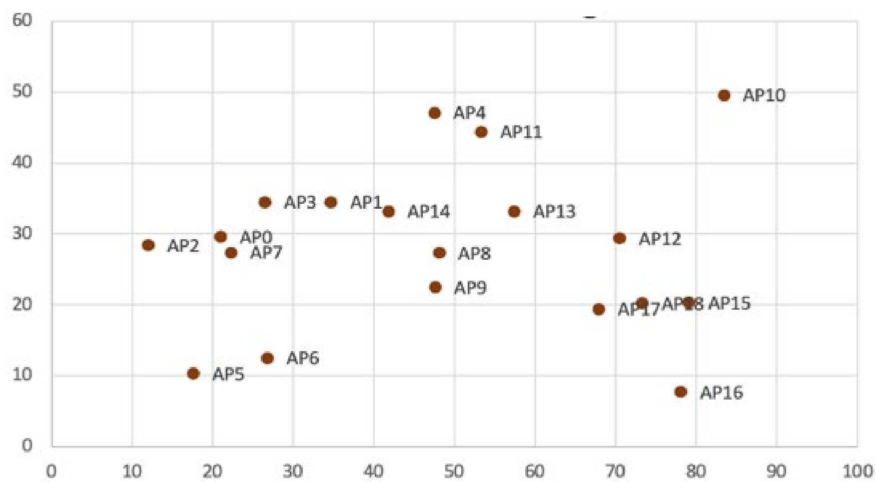

Figure 2A: First Implementation Approach – Average Error 12m

Conversely, the average error of just 4.4m that arises from the first implementation approach of presented techniques is depicted in Figure 2B, below.

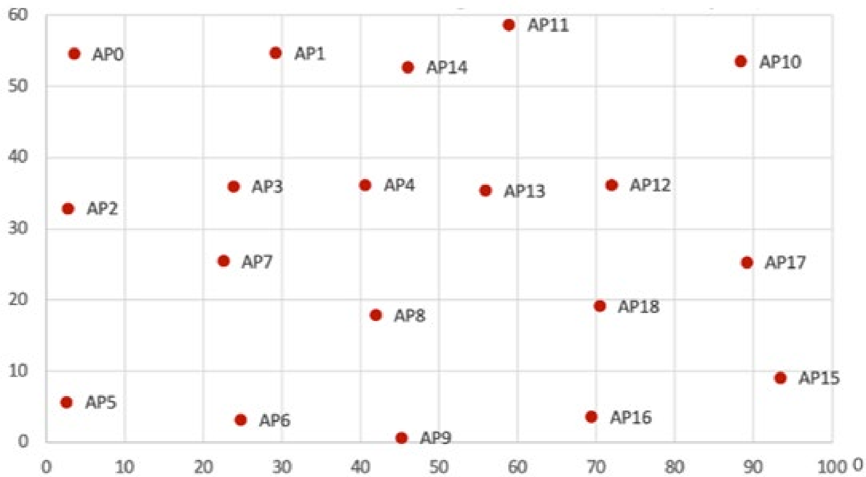

Figure 2B: First Implementation Approach – Average Error 4.4m

Figure 3, below, graphically depicts elements of the above discussion.

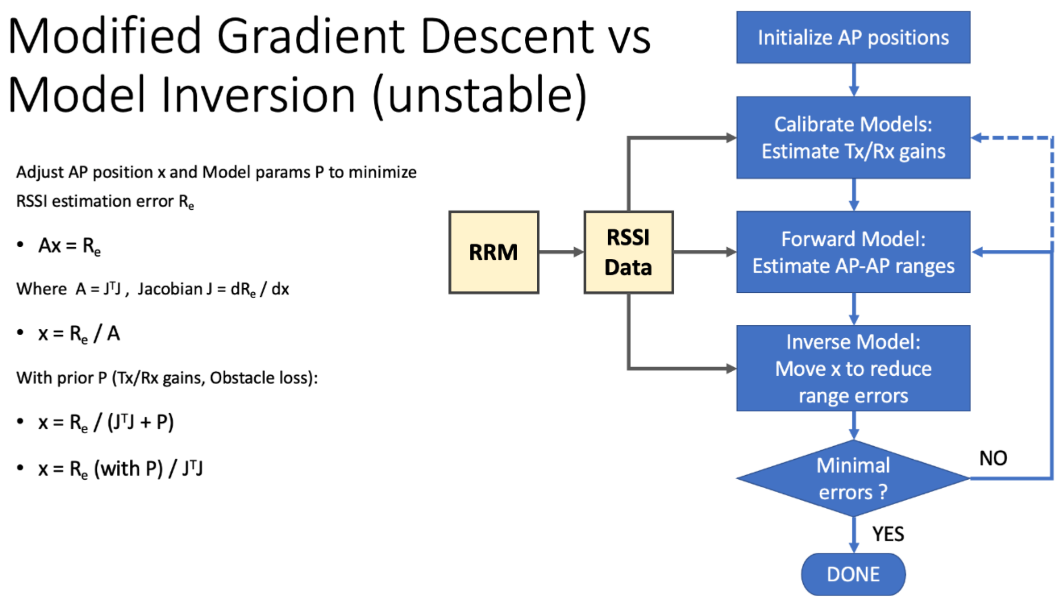

Figure 3: Exemplary Process Flow

According to the presented techniques, a second implementation approach encompasses the use of the fine time measurement (FTM) protocol, instead of RSSI data, to determine the location of an AP. The FTM protocol can provide higher ranging accuracy than a RSSI-based approach since FTM measurements are less affected by antenna gains and attenuations. However, those measurements are still affected by obstacles that block the direct signal paths. In many cases, a Wi-Fi signal may travel around the corner of a room (through, for example, a non-line-of-sight (NLOS) path) which results in the time-of-flight (ToF) between two APs ranging up to the square root of two (2) times longer than that of a direct (i.e., a line-of-sight (LOS)) path. Figure 4, below, illustrates aspects of the above-described NLOS path complexity.

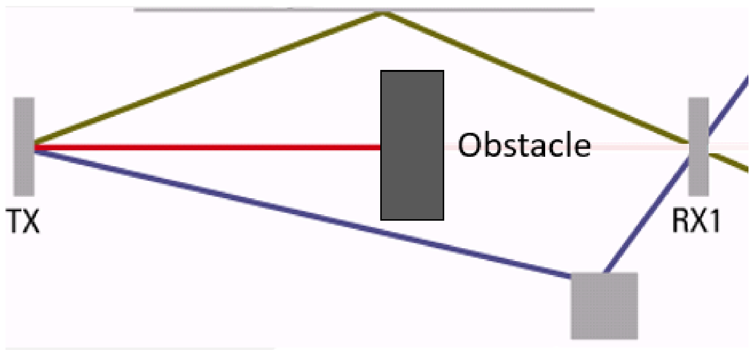

Figure 4: Illustrative NLOS Paths

It has been observed that FTM NLOS measurements are strongly correlated to the variance and asymmetry of FTM data. That observation leads to the following steps (as presented in Table 2, below) through which the presented techniques may detect and compensate for NLOS errors.

Table 2: Compensation Process

Step	Activity
1	FTM ToF measurements are collected between each pair of APs, in both directions, over some period of time.
2	The variance V_{ij} of the ToF from AP i to AP j is calculated over a time period.
3	The asymmetry S_{ij} of the ToF between each pair of APs is calculated as $\| ToF_{ij} - ToF_{ji} \|$.
4	If V_{ij} or S_{ij} are higher than a certain threshold, the AP pair i and j may be excluded from the location calculations.
5	V_{ij} and S_{ij} are used to calculate a calibration factor $C_{ij} = f(V_{ij}, S_{ij})$ where C_{ij} ranges between 1 and the square root of 2.
6	The calibration factor C_{ij} is used to calculate a range R_{ij} as (speed-of-light * ToF_{ij} * C_{ij}).
7	The location of each of the unknown APs is set to some estimated location – e.g., a best guess or some random value if unknown.
8	The known or estimated AP locations are used to calculate their estimated distances L_{ij}.
9	Given a range R_{ij}, trilateration or ML techniques are used to find AP locations that minimize the range error $\|\| R_{ij} - L_{ij} \|\|$.

As noted previously, more accurate measurement results may be obtained from a use of the FTM protocol than from RSSI data. This is because the FTM protocol converts a time to a distance using the speed of light (which is linear) while under a RSSI approach a signal strength measure is converted to a distance using a radio propagation model. Both RSSI data and the FTM protocol suffer from multipath issues which require a calibration step (using previously developed knowledge, if available). For example, the FTM protocol can provide approximately 1m of accuracy at 80 megahertz (MHz) in a LOS environment, but that accuracy stretches widely in a canyon scenario (i.e., a case where the LOS is obstructed by a strong obstacle but a reflected path is available). In buildings where the FTM protocol has been tested, such canyons can stretch the range by a factor of up to 1.8 without the RSSI data showing any detectable anomaly. Consequently, the presented techniques employ calibration (i.e., a merging of prior knowledge with current data) to improve the accuracy of FTM-based location results.

To illustrate the accuracy of the second implementation approach, consider the exemplary floorplan (containing a number of NLOS APs) that is presented in Figure 5, below:

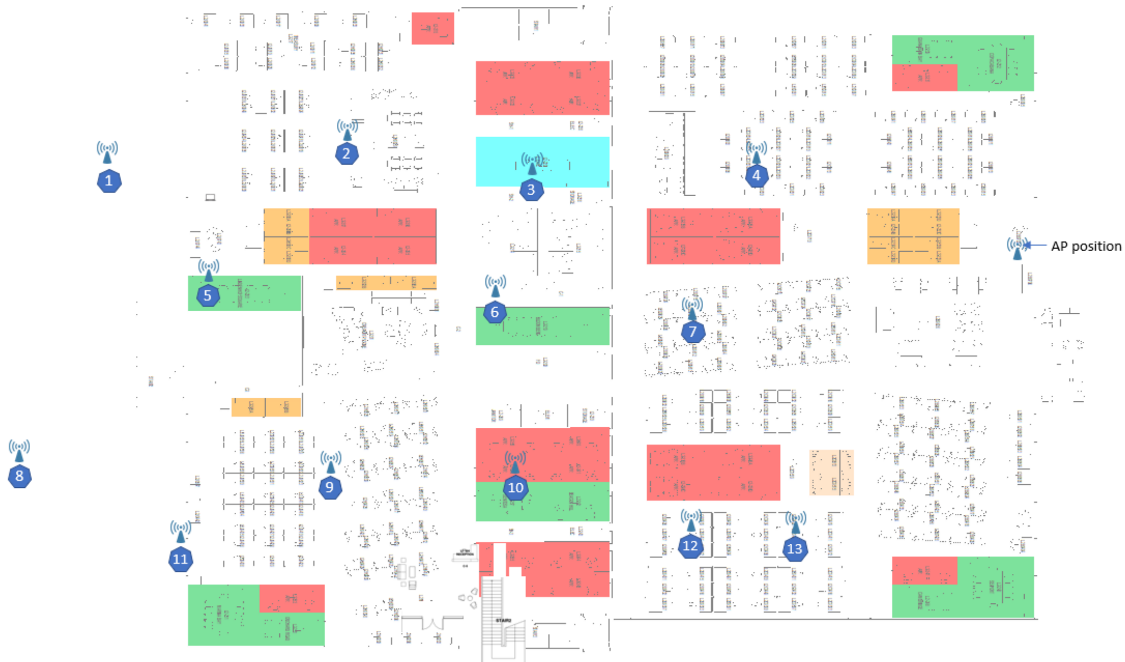

Figure 5: Second Implementation Approach – Exemplary Floorplan (NLOS APs)

Based on the above exemplary floorplan, the average error of 6.5m that arises from a conventional FTM approach is depicted Figure 6A, below:

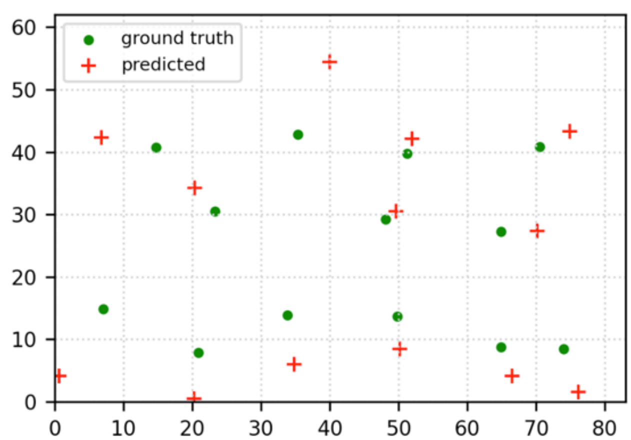

Figure 6A: Second Implementation Approach – Average Error 6.5m

Conversely, the average error of just 1.3m that arises from the second implementation approach of the presented techniques is depicted in Figure 6B, below.

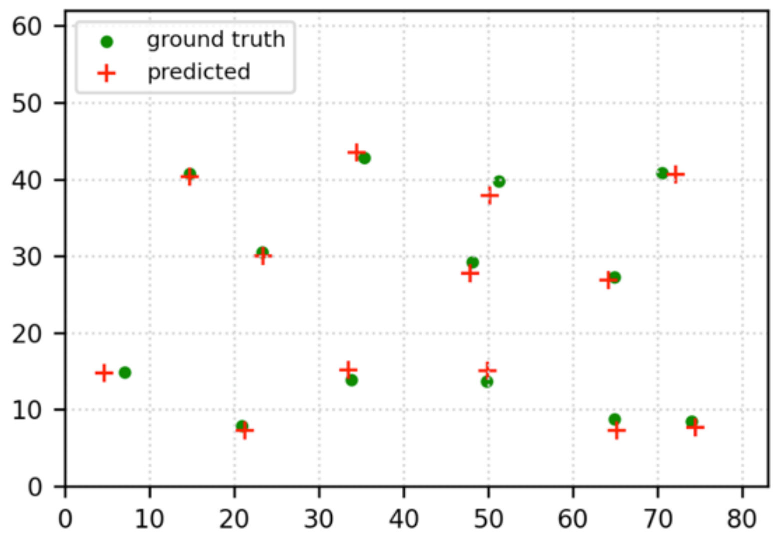

Figure 6B: Second Implementation Approach – Average Error 1.3m

To further illustrate the accuracy of the second implementation approach, consider a second exemplary floorplan (containing a number of LOS APs) that is presented in Figure 7, below:

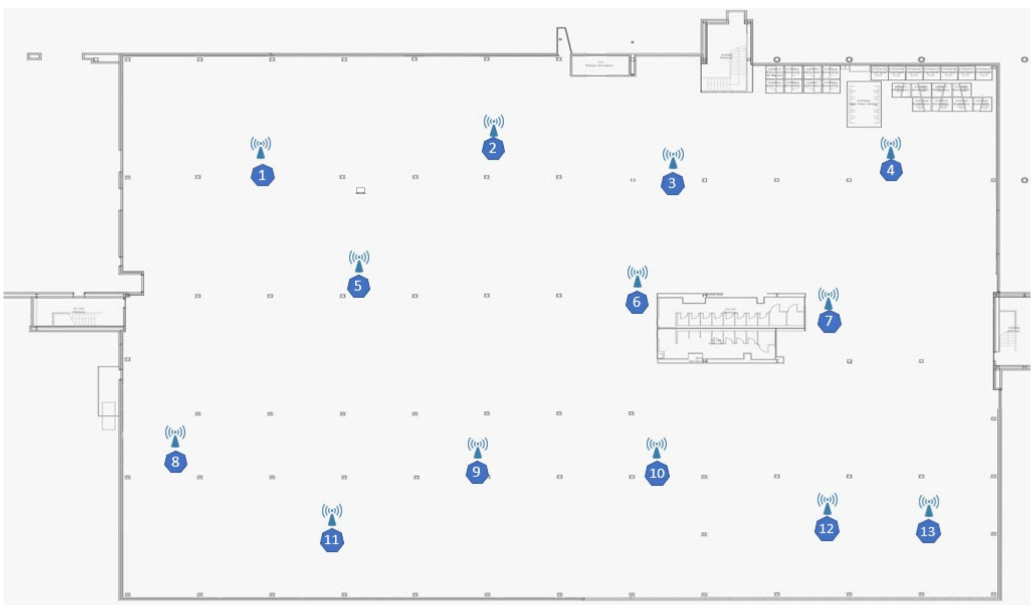

Figure 7: Second Implementation Approach – Exemplary Floorplan (LOS APs)

Based on the above exemplary floorplan, the average error of 83 centimeters (cm) that arises from a conventional FTM approach is depicted Figure 8A, below:

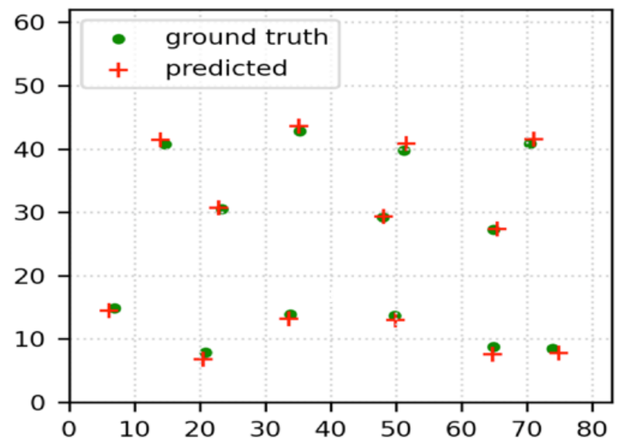

Figure 8A: Second Implementation Approach – Average Error 83cm

Conversely, the average error of just 17cm that arises from the second implementation approach of the presented techniques is depicted in Figure 8B, below.

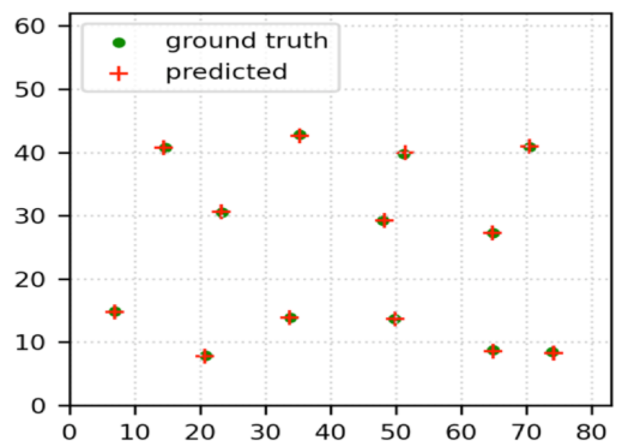

Figure 8B: Second Implementation Approach – Average Error 17cm

As demonstrated in the above discussion, leveraging FTM data may result in a more precise determination of an AP's location (on the order of, for example, under one foot for an LOS floorplan or an open space and approximately three feet for an NLOS environment) since FTM ranging produces a result that is naturally more accurate than RSSI ranging.

However, and importantly, the presented techniques, with their calibration features, can simultaneously address both RSSI and FTM data. In other words, given a deployment comprising a mixed universe of APs, some having a RSSI capability and some equipped with a FTM capability, the optimization capabilities of the presented techniques will work on these two measurement types. This is important since it should not be assumed that all APs are FTM enabled, as adding FTM support raises the cost of an AP. Competitively, it would be dangerous for a network equipment vendor to assume that the presence of FTM negates the use of RSSI. For example, a vendor's competitor could employ high-caliber RSSI chips, along with ML and artificial intelligence techniques, to achieve similar (i.e., FTM-like) results with a lower cost of goods sold (COGS).

It is important to note that although ML techniques are used in some solutions that attempt to solve the indoor AP location challenge, the presented techniques employ proprietary ML models that include unique and innovative methods such as, for example, sender and receiver gain estimations (K_i and E_j for RSSI data) and a calibration factor (C_{ij} for FTM data) as described above. Further, while some solutions require the presence of sensors whose location is known (where estimated positions are evaluated against those known sensor locations), the presented techniques do not impose such a requirement.

Consequently, and as described and illustrated in the above narrative, through novel methods and the incorporation of previously developed information (e.g., prior model calibrations) in the different calculations, the presented techniques eliminate restrictive requirements (such as, for example, a requirement for sensors) and provide more accurate AP location details.

In summary, techniques have been presented herein that support a new AP location identification method that uses prior model calibrations and ML techniques to detect an AP's location using either RSSI data or FTM protocol data. Among other things, the new method is faster and more accurate than conventional trilateration methods.