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DYNAMIC RE-CALIBRATION OF LOCATION USING ACTIVE SENSORS AND BEHAVIORAL ANALYTICS

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ABSTRACT

Techniques are described for using Wi-Fi® active sensors where the exact location is known. A Real-Time Location System (RTLS) compares a predicted location of devices with their actual location and measures the variance. Variance data is compared with the Radio Frequency (RF) metrics reported by the sensors at the time of measurement such that a regression model is created. Thus, based on the fully trained model, a correction factor for the RTLS algorithm may be determined at any given time and place in the Wireless Local Area Network (WLAN) to improve location accuracy.

DETAILED DESCRIPTION

Indoor wireless location analytics has improved in recent years through technologies such as Angle of Arrival (AoA). However, the accuracy of location measurements through Wi-Fi is notoriously inaccurate and unreliable, and the estimated location of a device can easily change as the Radio Frequency (RF) environment changes. As described herein, active sensors may be used as fixed points of continuous calibration of the location system. Further, behavioral analytics may be used to make a correlation between the differences of the estimated and actual location measurements with various RF metrics recorded at the times of location measurement.

Continuous comparison between the estimated and actual location of test subjects (the active sensors) may be made and entered in a digital twin, along with RF metrics collected at the time of each location estimate. RF data taken from the active sensors and the variance in the two location models (actual versus Real-Time Location System (RTLS) predicted) may be used to form a regression model that allows accurate estimation of the variance between the models at any given point. Dynamic re-calibration of the RTLS system may be made as the RF environment changes.

In a first example step, wireless sensor Access Points (APs) are deployed throughout a space. The exact location and co-ordinates of the active sensors may be measured and known. The active sensors may be treated as wireless test subjects by the RTLS. The RTLS may estimate the location of the active sensors at regularly scheduled intervals (e.g., every few minutes, ongoing, etc.). At each time of measurement, the active sensor may send a detailed RF snapshot to the RTLS, including Receiver (Rx) Received Signal Strength Indication (RSSI), Signal-to-Noise Ratio (SNR), Channel Utilization (CU), etc. Next, a simulation model of the space where the wireless network has been deployed may be used (e.g., in a digital twin).

The location of the sensor APs may constantly be re-evaluated so that an ML-based location system can be trained. The active sensors may be fixed devices and never move whereas the RF environment itself may be continuously changing. Sensor APs may be used as fixed location markers to provide continuous recalibration and training of the RTLS ML model.

In a second example step, the variance between the estimated and the actual location of the active sensors may be compared and measured. This may result in a variance value used to re-calibrate the RTLS measurements (comparing the estimated model and actual measured location).

Variance may be equal to the RTLS estimated location minus the actual known location (this is a Euclidian distance value, although the distance may be linearized by various means such as polar scale or log linearization).

One objective is to improve the estimated RTLS location using a Machine Learning (ML)-based training model that corrects the predicted measurement and can be used anywhere in the Wireless Local Area Network (WLAN). To do this, a correlation may be made between the variance (of the actual versus estimated models) and the metrics observed by the sensors in the RF environment.

The RF metrics collected from the active sensors may be used to create an n-dimensional hypothesis model, with the output being the variance in the location measurements. The collected RF metrics and the resulting variance between the models may provide a regression training set. With enough data collected, the model may be sufficiently trained and allow an accurate prediction of the variance depending on the real-time RF environmental measurements.

In one example, Variance(X) = AXi + BXi2 + CXi3 . . . . JXin. In this equation, the dimensions may be metrics such as RSSI, SNR, CU, etc. The weights of the variables may be learned based on the regression model. In addition, sensors may be leveraged to detect the proximity of the various class/types of stations in the vicinity and if the majority of the devices are from specific vendors then the sensors may focus on emulating such devices and determining how the variance is influenced by one type of device over another. That way, measurements from active sensors may be similar to that of real clients in the vicinity and may be used in the variance equation.

Based on the training set, the variance cost function may be minimized (gradient descent) such that the variance can now be estimated based on any new RF measurements taken anywhere in the WLAN.

The same exercise may be repeated for each sensor AP and entered into the simulation model.

In a third example step, the location tracking system may be re-calibrated in real-time. This may be an on-going step as new location estimates are made and the RF environment changes.

When a mobile client is examined for its location, the regression-based "corrected calibration factor" may be applied to the initial estimate of that client's location to produce a more accurate result of its actual location.

Although the correction may now be estimated with a high degree of accuracy when devices are in close proximity to sensor APs, the correction factor in the spaces between the sensor APs may now be extrapolated. Using the behavioral analytics model, RF measurements taken at any point in the WLAN may be used to identify the variance. Alternatively, a statistical model may be used to extrapolate variance numbers in the locations between the active sensors.

In the simulation model, the floor plan of the wireless coverage area may be divided into one square meter sections. Each square meter section may be assigned a re-calibration factor (+/- meters for both the x and y co-ordinates). These values may be continuously updated as the regression model is retrained with new data as the RF environment changes.

When the wireless location system now attempts to identify the location of a mobile device, the new correction values may be used. The estimated location of the client may be compared on the map, and the associated correction factor for that estimated location may be obtained. This may then be used to adjust the estimated location to a more accurate one. In one variation, the active sensor also returns the RF parameters of detected clients (in addition to the RF parameters of detected APs described in accordance with the first example step). This may introduce an additional correction value dimension, by altering the re-calibration factor based on the comparison between the client-to-active sensor computed value (from the AP value) and the client-to-active sensor computed value (from the client signal values reported by the active sensor).

Figure 1 below illustrates an example system for dynamic re-calibration of location.

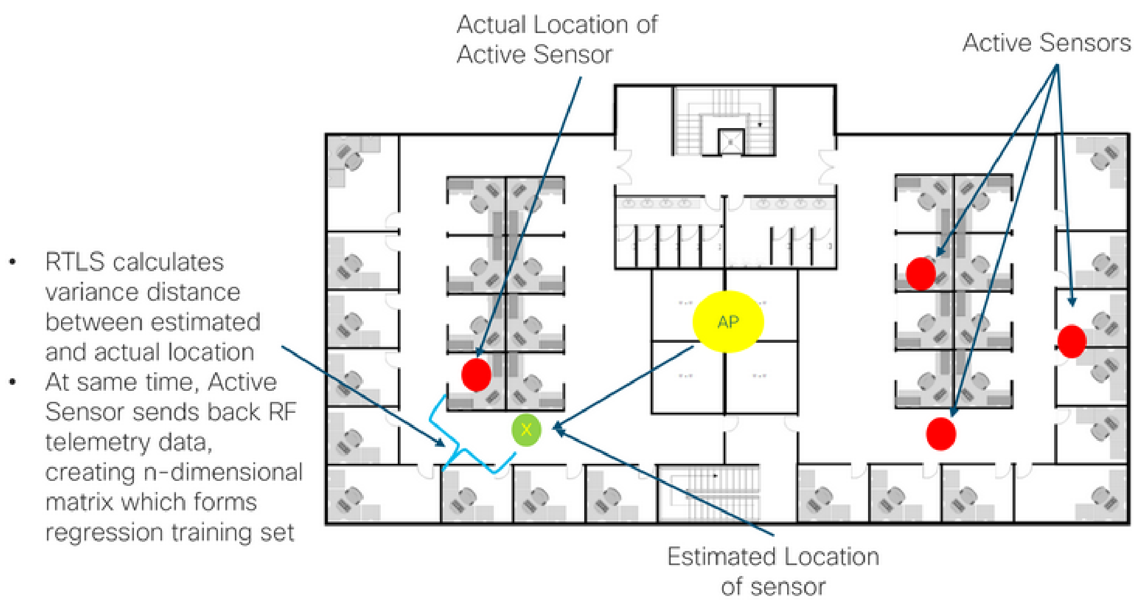

Figure 1

Techniques described herein may use fixed points that allow continuous calibration and extrapolation of the RF metrics that cause the estimated measurement to drift from the true location, thus resulting in an overall better prediction model.

An ML regression model may continually compare estimated (predicted) versus actual location variance against RF environment variables. This in turn may lead to a fully trained ML model that helps automatically recalibrate the system anywhere, thus improving location accuracy.

ML may be used to find the dynamic/changing relationships of the estimated versus actual location. The variables that caused the variance may be determined using ML. This may allow for extrapolation based on the same types of RF metrics and auto-correction or dynamic recalibration of the system based on the results of the ML model.

The techniques described herein are not necessarily specific to AoA. AoA is just one of many possible methods of RTLS. The techniques described herein may improve any/all types of RTLS using statistical ML / Business Analyst (BA) methods that learn, then try to auto-correct the ever changing variance observed in a predicted versus actual location model. Once trained, the regression model may be used to correct the predicted model by observing basic RF characteristics. Any simple model where deviation is assumed but is considered constant (or similar on all APs, all clients etc.) may be a simplification and apply to simple environments or conditions. As soon as environments become highly stochastic (e.g., changing client density, mobility etc.), a more advanced model such as that described herein may be preferable.

A ML/BA model may be leveraged to extrapolate the relationships between the RF environment variables and the variance between actual versus estimated location. This may help determine why the estimated location may be incorrect and also may help with auto-calibration. Fixed location devices like tags or sensor APs may be used as points to acquire data that is fed into the ML model where it is trained. From there, the ML regression model may determine the optimal correction factors anywhere in the WLAN (e.g., via a regression model). The ML training may enable improved auto-correction and calibration of the system based on the RF characteristic that are observed as they change over time. The variance may become an ML cost function that is minimized through the correction factor.

Using ML and statistical methods, a generalized model may be used to train any RTLS by continually comparing variance between actual versus predicted locations, then find the principal variables that are leading to the variance. This may result in an improved correction model that is applied to the predicted model, leading to superior location accuracy. Additionally, the sensor density may only need to be high if the estimation aims at validating short range changes of the signal. At a larger scale, it is understood that the measurement is not about instantaneous values, but about several samples (where the stochastic value difference will smooth out).

The predicted versus actual location variance of a sensor may be compared. RF environment data may then be used as the ML training set to predict a correction factor that can be used to automatically improve the accuracy of the RTLS.

In summary, techniques are described for using Wi-Fi active sensors where the exact location is known. A RTLS compares a predicted location of devices with their actual location and measures the variance. Variance data is compared with the RF metrics reported by the sensors at the time of measurement such that a regression model is created. Thus, based on the fully trained model, a correction factor for the RTLS algorithm may be determined at any given time and place in the WLAN to improve location accuracy.