Indoor Positioning Systems Using K-Nearest Neighbors

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## Abstract

GPS navigation applications on cellular phones and tracking an Amazon package online utilize real-time location systems (RTLS) to communicate critical location information to consumers. With a simple button press, users can track their packages and map routes to a destination. RTLS is also a component in inventory management and logistics for many different industries. Companies such as Dell Computer pioneered inventory management systems utilizing RTLS (Ojo-Osagie 1).

Another common use of a real-time location system is position identification inside of a room. These RTLS applications are called indoor positioning systems. In this paper, we investigate the effect of removing an access point on the accuracy of an indoor positioning system developed by Nolan and Temple Lang (2). We also improve upon their location determination methods by implementing a weighted *k*-nearest neighbors model for position identification. Results show that (results for MAC analysis here). Additionally, we find greater success using a weighted *k*-nearest neighbors approach in determining location.

## Introduction

Real-time location systems (RTLS) automatically track and identify the location of people or objects wirelessly. A classic RTLS example is location tracking of objects in a room. This RTLS application is called an indoor positioning system. Hardware such as bluetooth tags or cell phones are used as mobile beacons to communicate with strategically placed access points around the room. These beacons can be attached to people, other devices, and even robots (1). A beacon produces a signal that is read by the access points around the room. Each signal provides data used to determine the location of the mobile device within the room. Software applications utilizing triangulation, trilateration or a combination of location determination algorithms actively translate this location data and produce usable interfaces for people to identify the location of a beacon.

Applications for RTLS are vast and extend beyond a simple enclosed space. Advances in wireless technologies and proliferation of tracking tags have made real-time location systems ubiquitous in manufacturing, inventory management, and navigation (Winick 3). Identifying the current location of a package is a popular use of RTLS technology. Tracking previous location history and tracing locations to predict future locations are also common tasks. Additionally, active tags can provide critical data on the temperature of a package or the blood sugar level of a patient along with location information.

In this paper, we extend previous analysis by Nolan and Temple Lang (2) using indoor wireless signal strength data provided by Mannheim University. These data are generated from a single mobile device at 166 locations on one floor of a multi-story building. Eight orientation angles are considered at each location and 110 readings are taken for each (x,y) location, angle combination. Seven access points provide signal strength data to the mobile device.

In their analysis, Nolan and Temple Lang implement an indoor positioning system using signal strength data and an average-based *k*-nearest neighbors model. The model is used to predict the location of a mobile device using previously unseen signal strength data. The authors drop an access point from their training data set and use six of the seven access points for their *k*-nearest neighbors model.

We investigate the accuracy of the authors’ *k*-nearest neighbors model utilizing the access point previously not considered. We also extend the average-based *k*-nearest neighbors approach by implementing a weighted *k*-nearest neighbors model for predicting the location of previously unseen signal strength data.

## Literature Review

There are a multitude of techniques for RTLS to work such as radio frequency identification (RFID), infrared laser line-of-sight systems, and ultrasound systems. These systems allow for location data to be passed through objects or provide more precise indoor locations. The techniques used to analyze the position of the identification tags within each system can vary, as well. Though we utilize *k*-nearest neighbors in this paper, other location prediction methods are used depending on wireless tag communication protocols (Boulos, et al 4).

There are multiple uses for RTLS technology such as inventory management, livestock tracking, and personnel tracking. Healthcare has continued to develop ways to utilize such technology to limit cross-contamination. At the Toronto University Health Network, a real-time location system allows the university to locate personnel and equipment entering a contaminated area. The RTLS then sends an alert if the person or equipment hasn’t been decontaminated (Swedberg 5). Another example is a patent filed for tracking livestock that would assist ranchers and farmers in keeping location information on their herds.This system utilizes the distance value transmitted from the reader and k-nearest neighbor analysis to determine location (Chung 6).

RTLS research shows broad applications for *k*-nearest neighbors methods. The technology will continue to advance as businesses continue using RTLS to improve fulfillment requests using robotics and in warehouse distribution (Ding 7). Defense contractors utilize RTLS to assist in moving products from one location to another in their industrial processes to increase safety, efficiency and reduce human overhead (Hidalgo 8).

## Methods

In this paper, we investigate the impact of Nolan and Temple Lang’s decision to exclude an extraneous access point from their indoor positioning system. We also implement a weighted *k*-nearest neighbors model and compare it to an average-based *k*-nearest neighbors model they developed. Prior to discussing methods for accomplishing our two analysis objectives, we provide salient findings about the raw data and the transformations taken to prepare the data for analysis.

The raw data is split into a training set and a test set. We focus on the training data set for analysis purposes. The training data set contains 151,392 unique lines detailing the (x,y) position and orientation of a mobile device. At each position and orientation combination, 110 signal strength readings are obtained between the mobile device and seven access points. In addition to signal strength readings, variables such as the POSIX time of the reading and the physical MAC address for each access point are also captured.

After excluding extraneous access points, normalizing orientation values, and translating time variables, a dataset for analysis is created. The data set format can be seen in Table 1.

Table 1: Formatted Dataset for Analysis

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| time | posX | posY | orientation | mac | signal | rawTime | angle |
| 2006-02-11 07:31:58 | 0 | 0 | 0 | 00:14:bf:b1:97:8a | -38 | 1.139643e+12 | 0 |
| 2006-02-11 07:31:58 | 0 | 0 | 0 | 00:14:bf:b1:97:90 | -56 | 1.139643e+12 | 0 |
| 2006-02-11 07:31:58 | 0 | 0 | 0 | 00:0f:a3:39:e1:c0 | -53 | 1.139643e+12 | 0 |
| 2006-02-11 07:31:58 | 0 | 0 | 0 | 00:14:bf:b1:97:8d | -65 | 1.139643e+12 | 0 |
| 2006-02-11 07:31:58 | 0 | 0 | 0 | 00:14:bf:b1:97:81 | -65 | 1.139643e+12 | 0 |

Key exploratory data analysis results help to form assumptions and methods for an indoor positioning system using a *k*-nearest neighbors model. Non-normal, multi-modal signal distributions are found when considering signal strength and the angle of the mobile at each (x,y) location reading. This indicates angle has an effect on signal strength. Figure 2 displays this analysis finding for one access point at a single position.

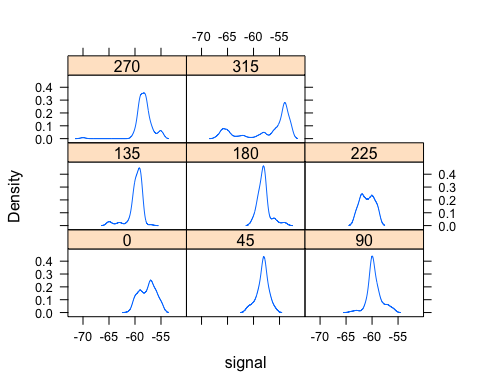


Figure 1: Angle Based Density Plots for 00:0f:a3:39:e1:c0

The transformed dataset is subsequently aggregated by (x,y) position, angle, and MAC address. Additional analysis using the aggregated data shows higher variability for stronger signal strengths. Also, the relationship between signal and distance shows that signal strength weakens as distance increases. This negative relationship is expected and can be seen for each access point in Figure 2.

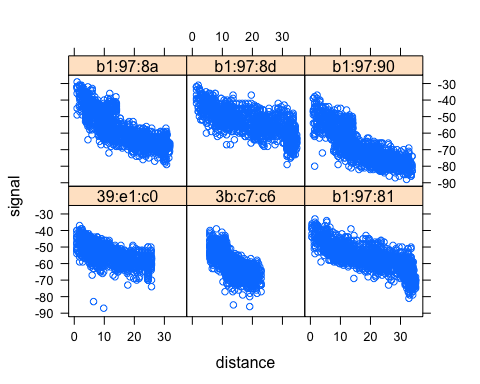


Figure 2: Relationship Between Signal and Distance

To prepare the training and test data for use in a *k*-nearest neighbors model, we aggregate records based on (x,y) position. Signal strengths from each access point for each position are mean-aggregated, forming a dataset where each record is unique based on the (x,y) position. Each position contains a vector of six signal strength values. A sample of this format can be seen in Table 2.

Table 2: Formatted Dataset for KNN Use

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| posXY | posX | posY | 00:0f:a3:39:e1:c0 | 00:14:bf:3b:c7:c6 | 00:14:bf:b1:97:81 | 00:14:bf:b1:97:8a | 00:14:bf:b1:97:8d | 00:14:bf:b1:97:90 |
| 0-0 | 0 | 0 | -53.47602 | -66.18943 | -64.53751 | -38.83086 | -65.91784 | -56.28203 |
| 0-1 | 0 | 1 | -52.90871 | -66.17718 | -65.91699 | -39.81460 | -65.51164 | -58.07841 |
| 0-10 | 0 | 10 | -55.25828 | -65.03161 | -66.36639 | -45.35057 | -65.78790 | -52.28319 |
| 0-11 | 0 | 11 | -54.16614 | -67.93829 | -68.84551 | -48.04929 | -66.55693 | -55.26282 |
| 0-12 | 0 | 12 | -54.45000 | -68.17850 | -70.83332 | -45.70979 | -68.29522 | -53.44322 |

Given previous analysis results, we assess the impact of Nolan and Temple Lang’s decision to exclude a MAC address on the accuracy of their *k*-nearest neighbors model. We also implement a weighted *k*-nearest neighbors model to predict location inside of the building.

*Analysis of Extraneous MAC Address*

Nolan and Lang’s work called for the exclusion of an extraneous access point which physically resides at the same location as the access point with MAC Address 00:0f:a3:39:dd:cd. This extraneous access point was excluded from the analysis presented in their text, as well as the initial knn analysis performed in our work.

Prior experience with triangulation of position based on sighting lines in land navigation leads to a general finding that additional measurement points will reduce the area of uncertainty of a position. Therefore, it could be hypothesized a similar effect will be achieved for an indoor positioning system that uses signal strength of known-position access points to locate an unknown receiver’s physical location.

Visual analysis of the relative signal strength of the two access points reveals a higher degree of certainty for the MAC Address 00:0f:a3:39:e1:c0. In the visualization below, the top two plots reveal signal strength for the retained MAC Address access point ending in e1:c0 from the angles 90 degrees and 135 degrees. The bottom plots repeat the exercise, this time for the access point ending in dd:cd, that was removed from the analysis by Nolan and Lang.

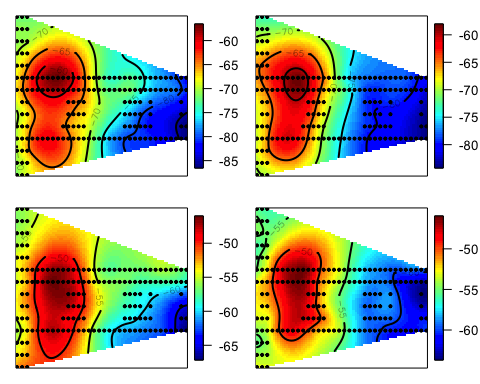


Figure 3: Signal Strength for Two Similar Access Points

## $`00:0f:a3:39:dd:cd`  
## NULL  
##   
## $`00:0f:a3:39:dd:cd`  
## NULL  
##   
## $`00:0f:a3:39:e1:c0`  
## NULL  
##   
## $`00:0f:a3:39:e1:c0`  
## NULL

To test the decision made by Nolan and Temple Lang, we will compare the results of the *k*-nearest neighbors process with three different training data sets. Formally, we compare the measurement of error between predicted location and actual location.

*Exclusion of the MAC Address Ending in dd:cd*

## [1] "results of original 1038.5"   
## [2] "results of original 6"   
## [3] "results of original c(1515, 1282, 1121, 1099.0625, 1093.28, 1038.5, 1066.95918367347, 1049.875, 1068.7037037037, 1099.86, 1102.61157024793, 1123.39583333333, 1150.76923076923, 1172.97959183673, 1195.90222222222, 1248.49609375, 1275.43944636678, 1331.52469135802, 1392.18836565097, 1433.17)"

Model results are established via cross-validation considering 11 folds and 15 locations sampled randomly for each fold. We establish a random seed to keep results consistent for each training data set considered. The metric used to compare results for each scenario is root mean square error.

Repeating Nolan and Temple Lang’s analysis by excluding the access point with a physical address of 00:0f:a3:39:dd:cd yields an optimal root mean square error of 1038.5 using six neighbors. The worst root mean square error of 1515.0 was produced by a *k*-nearest neighbors model considering one neighbor.

## [1] "results of new 935.611111111111"   
## [2] "results of new 6"   
## [3] "results of new c(1392, 1109.25, 959.333333333333, 950.0625, 953.88, 935.611111111111, 956.040816326531, 980.421875, 1003.16049382716, 1040.89, 1073.04958677686, 1098.125, 1123.15976331361, 1136.85204081633, 1162.38222222222, 1186.05078125, 1240.57093425606, 1294.20679012346, 1336.27700831025, 1380.23)"

Next, we execute the same nearest neighbors model excluding the access point with a physical network location of 00:0f:a3:39:e1:c0. However, we include the access point (00:0f:a3:39:dd:cd) previously not considered by Nolan and Temple Lang. Cross-validating our *k*-nearest neighbors model utilizing the access point previously not considered results in a minimum error of 935.6 given seven neighbors.

Reviewing the previous signal strength visualization, we hypothesize that the abrupt drop-off in signal strength offers a more discriminatory set of data to model against than an access point with very slowly decaying signal strength relative to distance. We investigate an average-based *k*-nearest neighbors model utilizing both access points next.

*Inclusion of Both Access Points*

## [1] "results of combined 1100"   
## [2] "results of combined 4"   
## [3] "results of combined c(1235, 1161.25, 1101.88888888889, 1100, 1175.64, 1267.69444444444, 1186.85714285714, 1174.90625, 1151.0987654321, 1180.89, 1208.3305785124, 1260.27777777778, 1311.57396449704, 1369.58673469388, 1396.04444444444, 1402.3671875, 1434.80276816609, 1496, 1571.82271468144, 1601.3925)"

Including both MAC addresses results in an minimum root mean square error of 1100.0 using four neighbors. Including both access points considered previously in the *k*-nearest neighbors model developed by Nolan and Temple Lang underperforms relative to models including one of the two access points. This can be clearly seen in Figure 4.

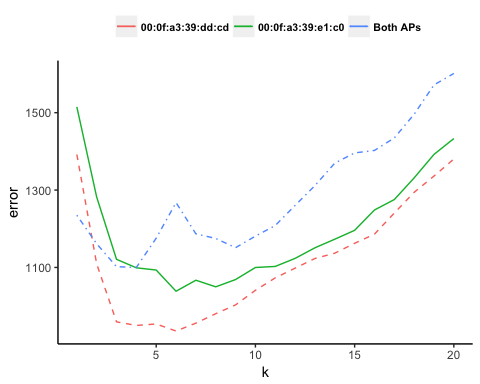


Figure 4: Learning Curves for Each Scenario Given K Neighbors

*Weighted K-Nearest Neighbors Implementation*

Nolan and Temple Lang implement a *k*-nearest neighbors model utilizing the mean of *k* known neighbors in the training data to predict the position of previously unseen records. These records contain signal strengths from six access points on the building floor.

Prior to model fitting, it is determined that the orientation of a reading has an impact on signal strength. For instance, when considering an x,y position of (2,12), MAC address 00:14:bf:b1:97:90 shows signal strength variability differences based on the orientation considered.

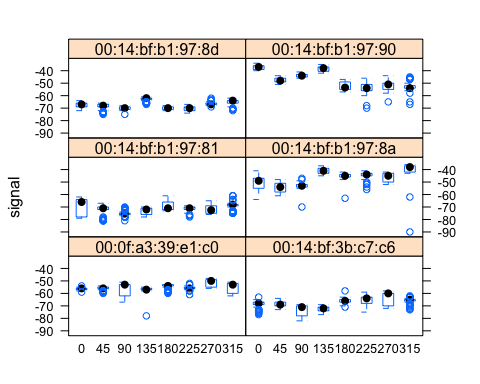


Figure 5: Angle Influence on Signal Strength for (x,y) Position (2,12)

The authors identify an angle parameter as part of their *k*-nearest neighbors model. This parameter allows the model to account for multiple angles when considering training set records for predicting the location of new observations. While we do not explore the angle parameter in our analysis, we note that three angles are considered when building the training data used for the *k*-nearest neighbors model. Thus, for every new prediction of location, a training set is created using three orientations. To maintain consistency, we preserve three orientations in our implementation of a weighted *k*-nearest neighbors model. This parameter value reduces bias and allows for multiple angles to influence the mean signal strength used for each observation in the training dataset.

Implementing a weighted *k*-nearest neighbors model requires weighting each training observation associated with the new location we wish to predict. New location in this task means a previously unseen vector of six signal strengths. Training observations closer to the new observation are weighted heavily, while training observations further away have smaller weights. The distance between any new observation and observations in the training data is calculated with Euclidean distance:

Equation 1: Euclidean Distance

Signal strengths (*S*) are considered for all six access points when calculating distance. This results in a distance calculation for each training observation given each new observation.

These distances are sorted in ascending order. Weights are calculated based on the choice of *k*, or the number of observations in the training set to consider when predicting the location for the new observation. Thus, the *k* neighbors are training observations taken from the sorted list of distances. In the example of five neighbors, we utilize the five closest training observations based on Euclidean distance to predict the location of a new observation. Each of the five training observations used for prediction are weighted according to Equation 2.

Equation 2: Nearest Neighbors Weighting

For each of the *k* training observations, the numerator is represented as one over the distance between the training observation and the new observation. The denominator is the sum of each numerator for the *k* observations we are considering. The first neighbor (k=1) is the closest to the new observation, therefore the weight associated with the first neighbor is always the largest.

Given previous weighting logic, we are able to form a vector of individual weights for each observation in the training dataset used for the *k*-nearest neighbors model. These weights are subsequently multiplied by the x and y locations of each *k* neighbor and summed to predict a weighted (x,y) position for the new observation. To ensure proper predictions, only the weights for each *k* neighbor is considered. All other neighbors assume a weight of zero. Given a new observation, the weight vector can be seen for three neighbors in Table 3.

Table 3: Weight Vectors for k=3

|  |  |  |
| --- | --- | --- |
| posX | posY | wts |
| 1 | 5 | 0.3831149 |
| 1 | 2 | 0.3221486 |
| 0 | 4 | 0.2947365 |
| 2 | 1 | 0.0000000 |
| 2 | 2 | 0.0000000 |

In summary, each new observation we wish to predict is compared to the training data set given the new observation’s orientation. This is the “lazy learning” for which *k*-nearest neighbors is known. A model is never fit to the data, we simply utilize the existing training data for prediction. A unique weight vector is formed based on the number of neighbors *k* and position predictions are obtained by multiplying and summing these weights for each training observation’s (x,y) position.

Nolan and Temple Lang’s average-based method considers the mean of each neighbor for prediction. This can lead to skewness in predictions as averages are not resistant to outliers. Weighting neighbors, on the other hand, partially corrects for the skewness seen using averages.

We formally compare our weighted *k*-nearest neighbors method to Nolan and Temple Lang’s average-based method

## [1] "results of weighted 1015.18690797938"   
## [2] "results of weighted 6"   
## [3] "results of weighted c(1515, 1273.10062016433, 1102.2642151606, 1074.24049747035, 1061.53124187946, 1015.18690797938, 1036.39248877713, 1020.09585266379, 1036.20625501185, 1058.22731631014, 1061.62041411801, 1079.9912721658, 1098.56798727289, 1111.42507300543, 1124.03691861609, 1162.29713712765, 1179.67441424646, 1218.73540618395, 1261.26747627927, 1288.91020846618)"

## [1] "results of weighted 908.383829087602"   
## [2] "results of weighted 6"   
## [3] "results of weighted c(1392, 1102.22032382265, 947.784671886505, 929.232476232528, 924.865965643884, 908.383829087602, 925.827592648343, 945.911072434793, 961.647005195819, 989.450730324949, 1015.22954669755, 1034.76182020886, 1054.63518260055, 1063.13579550405, 1078.29992254989, 1093.93844890613, 1135.02867277405, 1172.69749404752, 1202.2130366794, 1229.85792820128)"

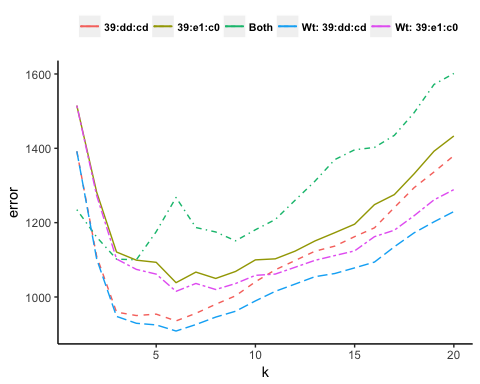


Figure 4: Learning Curves for Each Scenario Given K Neighbors

## Results

### *MAC Address Conclusions*

Nolan and Temple Lang’s decision to use the MAC Address of 00:0f:a3:39:e1:c0 and exclude the address of 00:0f:a3:39:dd:cd in their location analysis may have been predicated on knowledge of the hardware of the two devices and some difference in the performance. The signal strength visualization seems to lend credence to this idea. Visualizing a larger area of higher signal strength offered by dd:cd might suggest a lack of sensitivity between measurement of signal strength at different position if the strength of the signal decays more slowly or operates generally at a higher strength.

The failure of the inclusion of both MAC Addresses to improve error versus the inclusion of only the address of the access point ending in e1:c0 might suggest that the access points need to be dispersed, and generally lower powered if any gain in accuracy is to be gained from adding access points.

This might offer another line of investigation of the optimum coverage model for a desired confidence level in position. While it could be assumed that more access points will generally improve the performance of the location system, the placement of each access point is very important in managing the system. If this access point was placed elsewhere in the environment, the results would likely have been different.

### Weighted *k*-nearest Neighbors Implementation

To compare the weighted *k*-nearest neighbors model to the average-based *k*-nearest neighbors model

## Conclusions and Future Work

Indoor positioning systems help locate people or objects inside buildings or warehouses. This is achieved by sending information from sensors to mobile devices including tablets and smart phones. These systems use technologies many technologies: GPS, Bluetooth, Wi-Fi, and 4G/5G. A combination of these technologies leads to an object’s location with a goal of delivering a desired level of accuracy of the object’s position.

The ever-increasing availability of public Wi-Fi has helped RTLS expand its reach. Wireless devices are all built using similar manufacturing standards. However, wireless devices have a vast array of functionality. Therefore, it is important to understand the location accuracy differences that exist between tracking a user with a tablet, a phone, or a laptop. Further, environmental surroundings greatly impact the ability of locations to be predicted. Building materials or objects in the line of sight of a mobile tag can affect the accuracy of a signal and subsequently lead to mistargeting a location.

As seen in the analysis presented in this paper, there are multiple factors that can change the performance of a RTLS in a real-world environment. Within the limited example of a single floor of a multi-story building, we saw a difference in accuracy through the inclusion or exclusion of an overlapping access point. Exploration of the visualization of several access points showed obstructions changed the decay of signal strength. Real-world applications may have obstructions made from different materials with unique properties. While the test presented had just a single scanner for the entire test, a real-world application may need to provide a solution across several devices, or classes of devices to be nearly equally accurate.

Privacy concerns associated with real-time location services should be considered given the high level of precision offered as part of modern location determination technology. When a device is used to track a piece of equipment, one could surmise that the user of the equipment will generally be in possession of the device. This location then serves to track to the user throughout their work day. A recent patent issued to Amazon is for a wrist-wearable device that tracks a warehouse employee’s hands in real-time (Ong 9). Employees assume that the device is used as a measure undertaken to reduce errors in the picking, processing and shipping of customer orders. However, the employee can also view the device as an overlord, creating a running case for justifiable termination based on comparative productivity against other workers. Employees would likely not see an equal access to this data for their own cause. A company implementing RTLS employee trackers would likely protect the data against subpoena by binding arbitration agreements in the case of an on-the-job injury. Encryption may offer an additional measure of security and privacy protection. Yi, et al. propose to utilize the Paillier public-key cryptosystem during the query of the location given a *k*-nearest neighbors model. This provides the end-user with both location and enhances data privacy (10).

Real-time location services in retail could serve to reduce the intrusiveness of market-research activities conducted in stores. Firms, including VideoMining, have long used in-store video surveillance to monitor shoppers’ activities in store. While most consumers would generally expect that their activities in public are subject to observation, few shoppers might consider the existence of firms that will review footage and analyze the behavior of individual shoppers from the moment they enter the store. This analysis includes classification of the shopper based on their observed and perceived demographics (Hudson 11). Use of a RTLS tag on the shopping cart or basket could bring more anonymity to the process and eliminate the use of the video footage in this activity.

Recent advances in RTLS usage have been seen in the healthcare industry. Patient Room 2020 is a project led by the American Medical Association that uses RTLS to reduce inefficiencies (Bridges 12). The software tools help the administrators cut costs without compromising patient care or safety. The positioning system tracks a caregivers’ position to check on wait times and response times to the patients. RTLS can help identify efficiency gaps and workflow bottlenecks. An administrator can easily identify the closest caregiver to a patient room which clearly has an impact on operational efficiencies. However, given HIPAA regulations, data created by a real-time location system should be heavily scrutinized. It is important to promote benefits of RTLS and provide transparency to how the employer or system owner will use the data, as well as how the employer will safeguard and restrict the use or release of the data.

While real-time data collection is far from new, public understanding of this process has long had a weak foundation. One could argue that the public’s understanding of real-time location services will have a similarly long learning curve. As noted already, many areas of concern for privacy and data security already exist. An ethical framework is required for RTLS data as with all data collection practices. This framework should be based on the foundation of transparency to ensure efficient public understanding of data collection and retention policies.

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