Simulating Mobility Data Precision Requirements for Human Behavioral Inference

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1.0 Introduction

1.1 Motivation

Tracking and sensing of human activities is performed using a variety of techniques in an even wider range of applications. Healthcare policy makers [2], providers of online advertisements, and motion detectors all use sensors to infer the behavior of individuals or groups of people to achieve a certain purpose. These purposes are clearly very different, as are the types of information collected and their meanings. Systems designers encounter many choices for sensing applications, concerning what type of information to collect, by what method, and with what precision. This paper considers the precision requirements for a behavioral model that uses time-stamped location data. The goal is to develop and explore a method of quantifying the impact of mobility data precision on the accuracy of human behavioral modeling.

1.2 Application for Detailed Study

One specific application for behavior inference from individual mobility data may be to measure compliance by hospital or clinic staff with established hand washing regulations. With the incredible importance of cleanliness in a healthcare environment, it is important for hospitals and clinics to know that their staff members are keeping their hands clean – or, if not, to develop programs to increase compliance [1, 7]. There are many rules concerning when, and how, one's hands must be washed in this setting, and some of these rules can be applied to information about a person's movements over time. The application of these rules to mobility tracking data will constitute the model for study in this paper.

1.3 Expected Outcome

The developed model is expected to be extremely sensitive to the precision of the input mobility data. The same is likely to be true of the model's sensitivity to internal parameters concerning the formation and application of rules for interpreting behavior. These sensitivities will reflect the complexity of modeling human behavior, the arbitrariness of certain assumptions inherent to the model, and the need for very precise data for developing accurate models.

2.0 Background

2.1 Tracking, Sensing and Behavior Inference

Motion is sensed in many ways and on different scales [3] (see Figure 1, below). For example, navigational GPS (Global Positioning System) units in vehicles allow for a very large-scale tracking application to view movement over miles. At the same time, RFID (Radio Frequency Identification) sensors track packages and inventory in factories, stores, and libraries for motion over a few feet. Neither technology (GPS nor RFID) is suitable for the opposite-scale application. Precision is important, but how much is necessary for sensing significant events?

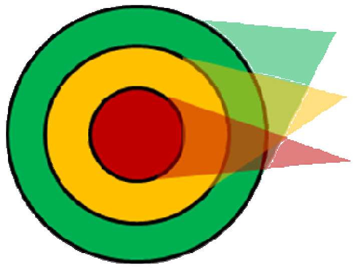


Figure 1 Scales of Sensing Human Motion and Example Methods

The answer to this question is clearly dependent on the model used to detect and measure significant events. The tradeoff between cost and precision of input data can also be analyzed as a tradeoff between cost and accuracy of model interpretation. RFID sensors lining every major road may provide more accurate sensing of the location of one's vehicle, but the marginally increased accuracy over GPS does not justify the considerably increased cost.

Tracking in this application appears to fall somewhere between the mid- and small-scales of human motion sensing. Different behaviors will be distinguished by locations of a few feet or less, requiring a high level of precision in mobility data. Certain behaviors (is this person washing his/her hands, or rinsing out a glass?) simply cannot be distinguished through *location* data, but these differences will be ignored for the sake of this paper.

2.2 Hand Washing Studies

Hospitals and health care researchers have a great deal of interest in improving compliance with hand washing guidelines among staff. While one of the simplest methods of preventing the spread of communicable diseases and patient infections, health care workers tend to average under 50% compliance[1] [4-8], and wash for less time than recommended [6]. Previous studies ([7], e.g.) have analyzed the effectiveness of campaigns to improve compliance, and revealed that staff members frequently overestimate the frequency of their own hand washing [1]. More frequent and/or more detailed studies may provide more insight into responses to pro-compliance campaigns.

Determinations of hand washing compliance do not occur more frequently in part because they are costly: studies are conducted by hiring observers to watch for recommended washing opportunities in high-risk areas [5-8]. An automated system for measuring hand washing could conceivably improve rates for many types of compliance by simply making data more frequently – or more individually – available. There are certainly many restrictions to the uses of such a system, as our models cannot (yet, at least) replace human intuition for which observed events meet certain criteria. However, a location-based system could, at the least, provide a starting

[1] It should be noted that guidelines for hand washing are intentionally very strict and very specific. Their rigidity makes it impractical to expect full compliance in a realistic setting. That said, health professionals have for years recognized the problems with such low compliance rates, and are actively engaged in improving them.

point for collecting and analyzing widespread data for many common situations in which hand washing is required.

Some specific guidelines (adapted from [1] and [5]) for hand washing will provide a basis for the model:

- Hands must be washed before contact with a patient during an examination.
- Hands must be washed after contact with a patient, before exiting the examination room.
- Hands must be washed immediately after use of lavatories.
- Hands must be washed for 10-15 seconds.

2.3 Uses and Limitations of GPS

The source of data for a hand washing detection system could be small-scale sensors, such as RFID tags (sensing a staff member's ID tag close to a sink), or more mid-scale technology, such as GPS. GPS (of some form) provides a tempting option, as the data may already be available through electronic devices. Specifically cell phones, which must be locatable in the event of a 911 call, employ tracking mechanisms. Location mechanisms in mobile phones are actually extremely precise when placed within clear sight of at least two cell towers. Indoors, however, cell phones – or any other GPS device – may not provide the desired precision and accuracy of information [3]. In a hospital, the accuracy of this data is weakened by attenuation (buildings), interference (hospital equipment), multipath (inside and between buildings), and location masking (through repeaters). By quantifying the impact of these inaccuracies on model fidelity, this paper should shed light on the requirements of the data collection mechanism(s) employed in a behavior modeling system.

3.0 Methodology

In order to assess the effect of data precision loss on the accuracy of a model, it was necessary to first develop a model for measuring hand washing compliance. This required (1) a method for representing contextual data (such as room and sink locations), (2) a construct for mobility data, (3) a set of rules for determining what data patterns constitute a required wash, an actual wash, etc., (4) a sizeable set of sample data to degrade and run through the model, and (5) an interface for loading mobility data and retrieving statistics. Item (1) is discussed in section 3.1.1, (2) is found in 3.1.2, (3) is covered in 3.2, (4) is described in □, and item (5) is demonstrated in section 3.4.

This section will describe the general approach to each step in building and running the model and data sets, as well as some details about the implementation. Unless otherwise noted, each software component was written in Java 6 SE and executed on a Windows platform.

3.1 Data Models

Models for representing the floor plan and tracked movement data shared certain characteristics that made the information easy to link during processing. Both models assume a simple Cartesian coordinate system in two dimensions. The models are dimensionless, but require integer coordinates. This leaves scale open and arbitrary, but easy to manipulate through linear scaling factors. The implication here is that any coordinate system should be transformable onto a grid, like the one shown in Figure 2, and that the tracking and floor plan data will be conveyed in the same scale for use on the same grid.

3.1.1 Floor Plan Modeling

The floor plan shown below in Figure 2 represents part of an actual clinic recently constructed in Sublette County, Wyoming [9]. This plan was used in all data generation and interpretation, but its presentation to the system was in a general form that could represent most floor plans. The floor plan model assumes that all rooms are rectangular, so that their regions can be indicated through the listing of only two diagonally opposite points. The grid overlay and highlighting in the image below were added manually.

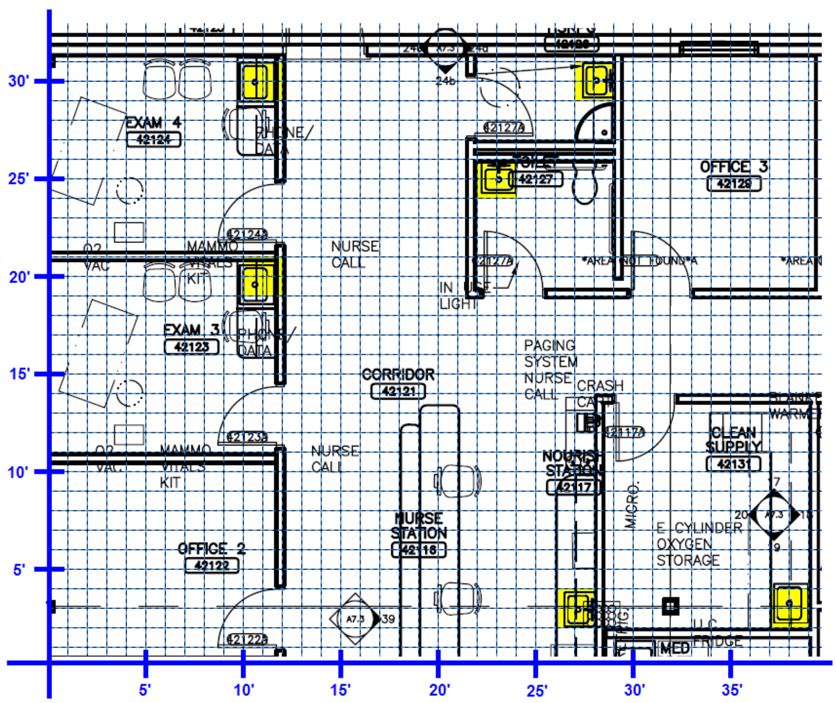


Figure 2 Floor Plan with Grid Overlay and Sink Highlighting

Shown below in Figure 3 is a textual representation of the same floor plan as show above, with a few adjustments. The first line of the file establishes a grid size for the entire floor plan. Each subsequent line lists the name of a location, the (rectangular) bounds on that location, and a *type*. Location *types* are used to identify different types of events so that rules may be applied accurately in the behavioral model. (That is, the rules that govern hand washing in an examination room are quite different than those for offices.) A class called *LocationManager* is responsible for reading in the floor plan data and creating *Location* objects for each room. The *Locations* include information about their regional limits, name, and type.

It is important to note that certain locations overlap, such as *Exam3* and *Sink_Exam3*. The model takes a hierarchical approach to "nested" locations, where locations listed earlier are given higher rank. The model assumes that one cannot enter a nested location without first (or simultaneously) entering the parent location, or exit a parent location without first (or simultaneously) exiting the nested location. Therefore, if an individual is observed using the sink in Exam 3, the model infers that s/he is in fact *in* Exam 3; if they then leave Exam 3, they must have also stopped using the sink. This is performed in the *LocationManager* by storing an ordered list of *Location* objects (highest order to lowest) for each point in the grid (which is simply a two-dimensional array). This approach, which is pointer-centric and therefore inexpensive from a storage point of view, translates any (x,y) coordinate into an ordered list of *Location* objects in **O(1)** time.

```
Total_Range: (0,0) to (39,31) none
Office2: (0,0) to (12,11) none
Exam3: (0,11) to (12,21) exam
Sink_Exam3: (10,19) to (12,21) sink
Exam4: (0,21) to (12, 31) exam
Sink_Exam4: (10,29) to (12,31) sink
Corridor2: (12,0) to (18,14) none
Corridor1: (12,14) to (22,31) none
Nurse_Station: (18,0) to (28,14) station
Sink_Nurse_Station: (26,2) to (28,4) sink
Corridor3: (22,14) to (39,19) none
Toilet1: (22,18) to (29,26) bathroom
Sink_Toilet1: (22,24) to (24,26) sink
Housekeeping: (22,26) to (29,31) housekeeping
Sink_Housekeeping: (27,29) to (29,31) sink
Office3: (29,19) to (39,31) none
Clean_Supply: (28,0) to (39,16) clean
Sink_Clean_Supply: (37,2) to (39,4) sink
```

Figure 3 Textual Representation of Floor Plan for System Entry

The major difference between the above file and the earlier floor plan is the inclusion of multiple "corridors," which are in fact three rectangular regions (subject to the restriction mentioned earlier[2]) that together comprise the entire hallway of the clinic.

3.1.2 Tracking Data

Tracking data utilizes the same grid as the floor plan data. Each entry consists of an individual identifier, a time (arbitrary, integer units; generally assumed to be seconds), an x-coordinate, and a y-coordinate. Coordinates are subject to the same restrictions as the points of the floor plan:

[2] The restriction was made for the sake of simplicity. It is not an inherently necessary part of the model; rather, it assists with verifying that a point falls within the bounds of a known location. The modifications needed to remove the restriction are not terribly difficult; they are, however, entirely unnecessary for the floor plan used.

they must fall within the grid boundaries specified in the first line of the floor plan input file, and they must be integers. The addition of a unique identifier with each point makes possible the inclusion of data for an unlimited number of individuals in a single file (as shown in the sample file section below in Figure 4). Each individual is represented by a *User* object, which handles the addition of each new tracking point for that individual. The function of *User* objects is described more fully in the next section, 3.2, which covers the behavioral model.

7	30	6	25
3	32	14	9
4	32	6	15
5	32	12	13
6	32	10	29
3	34	14	11
5	34	8	13
6	34	10	29
2	36	26	2
3	36	13	13
5	36	8	13
6	36	10	29
9	36	11	29
3	38	10	12
5	38	8	
6	38		
9	38		

Figure 4 Sample Tracking Data for Multiple Users

3.2 Behavior Model

The operation of the behavioral model is demonstrated in Figure 5, below. As tracking data points are given to a *User* object, the *User* asks the *LocationManager* for a list of *Locations* associated with the point. At each step, the *User* keeps track of its last *Locations*, so that *Events* can be generated when any *Location* changes occur. *Event* objects have start and end times, an associated *Location*, and a *type*. *Event types* include the entrance into an examination room, exiting an exam room, starting a hand washing, etc. One conceptual "event," then, is represented by two *Event* objects. For example, a patient examination will consist of a "start examination" event and a "stop examination" event. Both events will have the same start and end times, but by storing *Events* in the order they occur, conceptual events can be nested properly (see the explanation of nested locations in section 3.1.1, above).

There are two major advantages to this approach. First, it is concise and intuitive: rather than an arbitrarily large number of location data points representing an individual's time spent in one location, the entire duration is described in two symmetrical *Event* objects (the start *Event's* end time is updated with each new point, but no new objects are created). Second, the symmetry of events makes the application of *Rules* (described below) much simpler: both the start and end of a conceptual event are demarked by chronologically accurate *Event* objects. For example, determining which events ended after another began involves a simple linear search for ending *Event* objects ordered after the start *Event* in question.

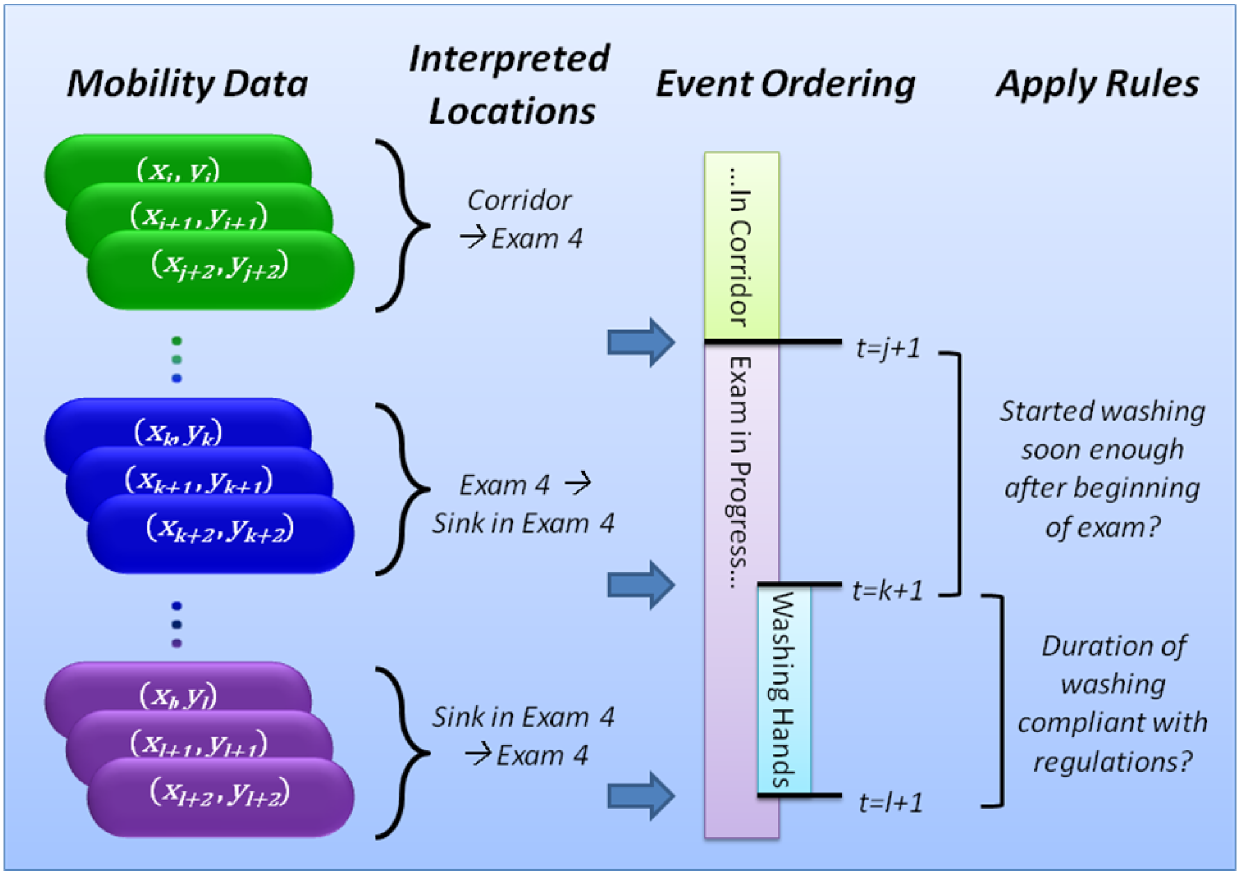


Figure 5 Steps in Compliance Analysis from Mobility Data

Rules are designed to be flexible, if not generic. The objects are described by a six-tuple:

- Trigger event type – the type of event that triggers a hand washing requirement
- Trigger event duration – the minimum duration of the trigger to require a hand wash
- Before or after trigger point – direction in which to apply time window (before or after)
- Trigger start or end – point from which to apply time window (start or end of event)
- Time window – time during which a hand washing event must either begin, or end
- Compliant event duration – time spent at sink to count as a compliant wash

An example rule states that if a started examination lasts more than 120 seconds, a hand wash event of at least 10 seconds in duration must begin within 40 seconds after the start of the examination. The rule is represented as

- Trigger event type = start exam (i.e., individual enters examination room)
- Trigger event duration – 120 seconds
- Before or after trigger point – after
- Trigger start or end – start
- Time window – 40 seconds
- Compliant event duration – 10 seconds

The *Rule* definitions and the structure of the *Event* list allow “before” events to be searched for in reverse order, and “after” events to be discovered in normal order. Each *User* object has a *Statistics* object that contains information about how many “opportunities” (i.e., required hand washing events) were observed, how many “actual” (compliant) hand washes occurred at opportunities, as well as the number of “additional” (no matching opportunities) hand washes were found for the list of *Events* the *User* experienced. *Rule* and *User* objects are together responsible for updating the *Statistics* object of a *User*, given a *Rule*, a list of *Events*, and an old *Statistics* object.

3.3 Data Generation

A software tool was developed to randomly generate sample tracking data for a single person. The tool reads in a floor plan using a *LocationManager* (as described earlier in section 3.1.1), but additionally requires sinks to be listed immediately after the rooms in which they are located in the input file (this requirement is met by the sample input floor plan show earlier in Figure 3). The *DataGenerator* object keeps separate lists of *Locations* by type (examination room, bathroom, or other non-sinks) as well as matching sinks with each examination room and bathroom.

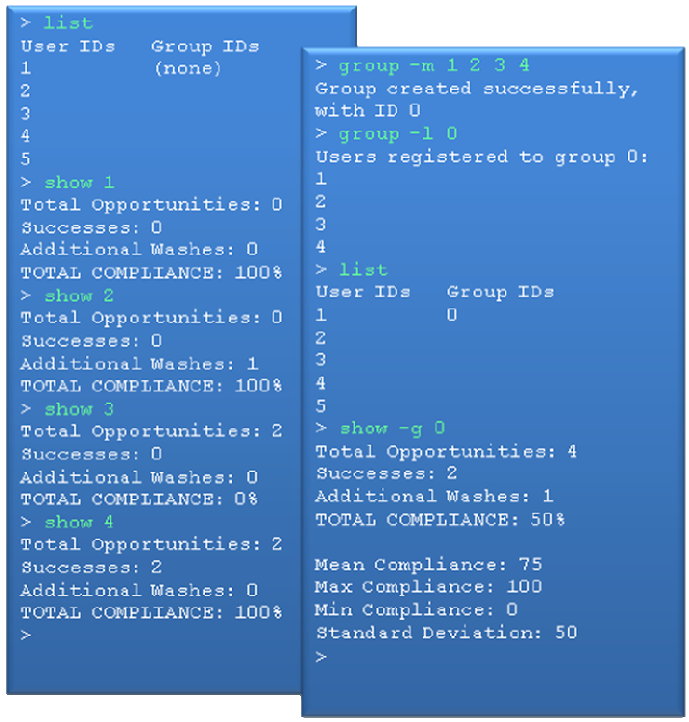
Data is generated by randomly selecting a *Location* type (examination rooms are more likely to be selected than bathrooms, and both are more likely than other types), and then choosing a *Location* uniformly from among the available *Locations* of that type. If the *Location* chosen is a bathroom or examination room, a random number decides if the individual will start or end his/her time in the *Location* by washing his/her hands (that is, at the sink associated with the room) so as to comply with hand washing guidelines. If a sink is not chosen as the starting point, the individual begins in the center of the room and moves according to another random distribution (each point is written to an output file). The duration of time spent in each room is determined when the *Location* is chosen. *Locations* continue to be chosen until a specified amount of time has elapsed in the simulation. The format of the output file matches the requirements for loading it into the model for analysis.

3.4 Interface and Statistics

A text-based interface is used to control the software system and read the generated statistics. Upon execution, the software opens a file chooser dialog to ask for floor plan data, then for the tracking data to load. Once successfully loaded, the command line interface becomes active, with commands available as shown in the help file, copied in Figure 6 below.

```
help                         -- show this help file
list                         -- show a list of user and group entries
show <n>                     -- show statistics for user with ID n
show -g <n>                  -- show statistics for user group n
group -m <n> <n> ...         -- make a new group for users with IDs n
group -l <n>                 -- list user IDs in group n
group <n> -a <m> <m> ...     -- add users with IDs m to group n
group <n> -r <m> <m> ...     -- remove users with IDs m from group n
group -d <n>                 -- delete group n
reload                       -- rerun the loading prompts
<quit|exit>                  -- leave the simulation
```

Figure 6 Text-based GUI Help File



After data is loaded, the <list> command will show all individuals (and groups) for which data is available. The <show> command will print out the statistics. Individual statistics include hand wash "opportunities", "successes," and "additional" washes along with a computed rate of compliance. Groups can be added, changed, and removed at will. In addition to the collective compliance statistics shown for an individual, group statistics show mean, minimum, and maximum compliance rates among individuals in the group, as well as the standard deviation.

4.0 Results

4.1 Parameters for Generated Data

Eight hours of tracking data for a single staff member were generated stochastically using the generation tool described in section 3.3, based on the floor plan input file shown in Figure 6. Table 1 below shows the value of the probability parameters that describe where the user is likely to go, for how long, and with roughly what level of hand washing compliance. Properties describing location type and compliance were described in section 3.3. The coordinate change distribution describes how likely the individual is to move away from their current location (the probability is applied separately to the *x*- and *y*-coordinates, positive and negative directions are applied uniformly). Finally, time spent in each location was determined by choosing a range (0-5min, 5-10min, 10-15min) based on the probabilities shown below, then choosing a time uniformly from within that range.

Property	Probability	Property	Probability
Location type = exam	0.5	Comply on exam enter	0.68
Location type = bathroom	0.3	Comply on exam exit	0.51
Location type = other	0.2	Comply on bath exit	0.73
Coordinate change = 0	0.60	Location time < 5 min	0.3
Coordinate change = 1	0.20	Location time < 10 min	0.9
Coordinate change = 2	0.12	Location time < 15 min	1.0
Coordinate change = 3	0.08		

Table 1 Probability Values for Stochastic Tracking Data Generation

Data was then additionally transformed to represent degradation in location data precision. That is, a single set of source data was used to compute degenerate data across three levels of lower precision. The stochastically produced file was generated at a resolution of 1'x1'. An Excel spreadsheet was used to modify this data so that it mapped onto points in a 2'x2', 3'x3', or 5'x5' grid. Each data point was mapped to the closest, lower integer multiple of the dimension at hand (in a form similar to *x_new=FLOOR(x_old/dim)*dim*), and then shifted to a point within its newly assigned *dim*x*dim* square. All permutations (4 for 2'x2', 9 for 3'x3', and 25 for 5'x5') were computed and run through the model. The statistics graphed in Figure 7 and Figure 8, below, use the average of all permutations for each precision level.

4.2 Rules

There were three rules for hand washing applied to the data for each precision level. They are defined below in Table 2, according to the method described in section 3.2.

Parameter	Rule 1	Rule 2	Rule 2
Trigger Event Type	Start Exam	End Exam	End Bathroom
Trigger Event Duration	120 seconds	120 seconds	20 seconds
Before or After Trigger	After	Before	Before
Trigger Event Point	Start	End	End
Time Window	40 seconds	40 seconds	15 seconds
Min. Wash Duration	10 seconds	10 seconds	15 seconds

Table 2 Rule Definitions for Examined Data

4.3 Computed Statistics

The data below in Figure 7 show the average required ("expected"), successful ("actual"), and additional hand washing events that were measured by the model at each precision level. The full data may be found attached as Appendix A. The data at one square foot of precision is taken as "reality." There are clear discrepancies as soon as precision drops to just four square feet.

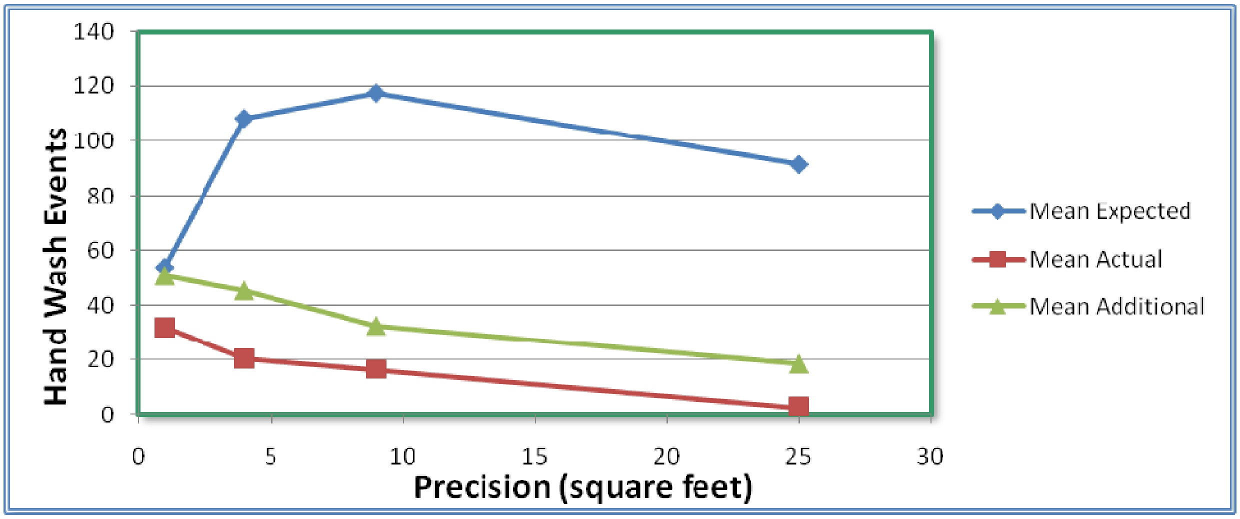


Figure 7 Interpreted Hand Wash Events vs. Tracking Precision

There are two trends clear in the graph above. First, the loss of precision causes the model to believe that *more events occurred* that should generate a required hand washing than actually did. Second, the loss of precision causes the model to believe that *fewer hand washings occurred* than really did, whether to comply with requirements or just additional washes. The second trend is easier to explain. The sinks given are only 2'x2', and the model requires a location inside that region for the event to count as a hand washing. At all precision levels larger than 2'x2', each sink will be completely unreachable in at least some permutations of the grid cluster offsets. Even for the 2'x2' grid, data points representing valid hand-washing events are likely to have at least a few points hop off the sink long enough to end the wash early.

The increase in expected washes is not as intuitive. Again, this relates to the sensitivity of the model. There is nothing in the model to stop a tracked user from travelling, apparently through walls, back and forth into adjacent rooms. If an individual is supposed to be in examination room 3 (see Figure 2) for 10 minutes, for example, that individual would normally be responsible for two hand washes: once at the start and once at the end. However, if that individual approaches the walls of the examination room just over every two minutes, the distortion in data at lower precisions could give the appearance of someone momentarily leaving, then re-entering, the room. Every two minute or longer period in the exam room, capped by a departure into and return from another room, yields another two required hand washes. The trend reverses at very low precision: if more "false exits" are being generated, then there will be fewer two minute stretches during which the individual appears to be in one room, than observed at higher precision. As there is no such distortion in the 1'x1' case, these phantom exits will never occur.

The contrast between the measured compliance rates for the 1'x1' case and for the other three cases (Figure 8, below) is explained by computing compliance from successful washes (fewer than expected were measured) divided by required washes (more than expected were measured).

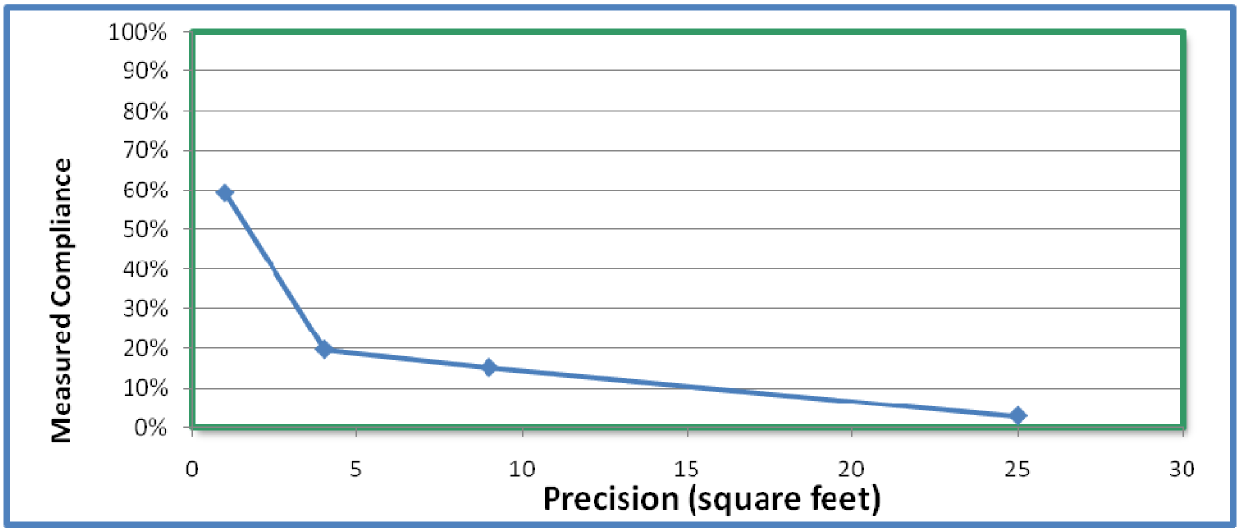


Figure 8 Measured Compliance vs. Tracking Precision

5.0 Implications and Future Work

The results given in the previous section must be analyzed with respect to the limitations of the model used. For example, it seems that it would not be difficult to adjust many of the model parameters (specifically, the details of the floor plan and the rules used to determine compliance) to get a fairly accurate result with precision down to four square feet (2'x2'), as the sinks in the example floor plan are taken to be in regions of 2'x2'. Without having gone through the exercise of "tuning" the parameters of the model for each precision level, it is difficult to assess (indeed, it would still be difficult to quantify) the complexity involved in making these adjustments. The point here is that no claim of "location data must have a precision of one square foot to measure this kind of behavior" can be made generally. This only holds true for the limited, often simplistic model used.

It is still useful to say, however, that there are obvious implications for model integrity with diminished precision. Someone interested in building a real system to measure hand washing compliance using location data should be able to adapt the tool that was developed to determine their own precision requirements. The results make it clear that not "just any data will do" – the raw data and the model interpreting it must be tightly connected. It may also be possible to say that a single model cannot operate over a wide range of precision levels, at least not without significant adjustments for each level.

Future work building on the project presented in this paper could take on the task of tuning the model definition and determining the most effective way of dealing with imprecise data. Simple filters may remove some obviously erratic data, while far more advanced models could apply rules that make it impossible for someone to pass between walls without doors in short time periods (as appeared to be the case in the results presented). A more realistic data set, perhaps from observing a hospital worker's movements, might provide insight into more of the intricacies of movement and the nature of hand washing in a real environment. Additionally, a more intelligent algorithm might "learn" the parameters for modeling behavior through training data that provides event information (room entrances, exits, hand washing, etc.) in addition to the raw mobility data. Finally, the results of this or a follow-on paper could be coupled with measurements of the precision of real systems to demonstrate what specific types of sensors could be reasonably deployed in the example (or a related) application.

6.0 Conclusion

Human behavioral models make many assumptions – this is the primary way that data is interpreted. One of the assumptions implied in most models is that the data being interpreted is accurate and precise enough to make such assessments concerning the behavior of observed individuals. Even the most accurate data still leaves out enormous amounts of information concerning the reality of the observed events. The intricacies of human behavior cannot be fully expressed in a model as simple as the one observed here. Therefore it is impractical to expect perfect results from any model, so there is an inherent threshold of accuracy below 100% that must be accepted if any models are employed. The cost of diminished precision, therefore, may not be substantial if the accuracy is *good enough* to learn something useful from the tracking data. This is especially true when financial considerations make a less precise system far more viable. It is hoped that the tools and methods developed in this paper will be able to assist with such cost-benefit analyses in future systems developments.

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Appendix A

Scale	Horiz. Offset	Vert. Offset	Opps	Actual	Additional	Compliance
1	0	0	54	32	51	59.26%
2	0	0	89	19	41	21.35%
2	0	1	82	20	49	24.39%
2	1	0	132	21	42	15.91%
2	1	1	130	22	50	16.92%
3	0	0	136	0	4	0.00%
3	0	1	148	0	0	0.00%
3	0	2	92	0	2	0.00%
3	1	0	91	11	30	12.09%
3	1	1	90	37	65	41.11%
3	1	2	102	26	50	25.49%
3	2	0	139	10	31	7.19%
3	2	1	157	39	63	24.84%
3	2	2	102	26	50	25.49%
5	0	0	70	3	22	4.29%
5	0	1	98	0	0	0.00%
5	0	2	98	0	0	0.00%
5	0	3	114	0	0	0.00%
5	0	4	120	13	51	10.83%
5	1	0	70	3	22	4.29%
5	1	1	98	0	0	0.00%
5	1	2	98	0	4	0.00%
5	1	3	114	0	4	0.00%
5	1	4	120	13	51	10.83%
5	2	0	78	2	21	2.56%
5	2	1	113	0	0	0.00%
5	2	2	113	0	21	0.00%
5	2	3	92	0	21	0.00%
5	2	4	92	17	82	18.48%
5	3	0	78	2	21	2.56%
5	3	1	113	0	0	0.00%
5	3	2	113	0	17	0.00%
5	3	3	92	0	17	0.00%
5	3	4	92	17	82	18.48%
5	4	0	54	0	0	0.00%
5	4	1	57	0	0	0.00%
5	4	2	57	0	17	0.00%
5	4	3	72	0	17	0.00%
5	4	4	72	0	0	0.00%