eDOTS 2.0: A Pervasive Indoor Tracking System

Ryan Rybarczyk, Rajeev Raje, Mihran Tuceryan
Department of Computer and Information Science
Indiana University Purdue University Indianapolis
Indianapolis, Indiana USA
{rrybarcz, rraje, tuceryan}@cs.iupui.edu

***Abstract*— Designing tracking systems that cover large indoor areas and encompass different sensor modalities pose many significant challenges such as multi-sensor data fusion, coordinate system handoff and associated transformations. In this paper, we present the design and implementation of a prototypical system that effectively tackles these challenges. The proposed system is empirically validated in a laboratory setup and results of these experiments are also presented in this paper.**

Keywords-pervasive tracking, indoor tracking systems, multi-sensor data fusion, heterogenous tracking, sensor subset selection

I. INTRODUCTION

Indoor tracking is of critical importance in many futuristic application domains such as personalized health care setups in homes and assisted living centers. Typically, these application surroundings will contain deployments of multiple types of sensors (e.g., vision-based, Wi-Fi, etc.), each possessing different characteristics. Multiple types of sensors are necessary in these setups as each type may complement others, may provide a better coverage of a large indoor area, and overcome partial failure of sensors. Designing an effective pervasive indoor tracking system in such heterogeneous sensor-based setups requires tackling of following scientific challenges: a) the fusion of different types of location data obtained from various sensor modalities, b) a seamless handoff between different coordinate systems and associated transformations, and c) the dynamic nature of the indoor setup. This paper tackles the first two challenges, while the third challenge is considered as future work. Hence, specific contributions of this paper are: a) a development of effective techniques to tackle the first two challenges, and b) an empirical validation of these solutions by creating a prototypical system. The prototypical system is called the eDOTS (Enhanced Distributed Object System) 2.0 and it is an improved version of a preliminary prototype called eDOTS 1.0.

II. ENHANCING AN INDOOR TRACKING SYSTEM

The eDOTS 1.0 [9,17,18] was developed in an effort to provide an indoor tracking framework made up of one type of sensors, specifically, vision-based sensors. This framework utilized web cameras and the ARToolkit API [7,12,14] for the ability to track marker patterns. The eDOTS 1.0 made use of various data fusion techniques (e.g., averaging, Kalman filtering, etc.) to provide an estimate of an object's location from different location readings. Due to the stringent time sensitive requirements of data fusion, the underlying issue of clock synchronization was also addressed in the prototype. More information regarding the eDOTS 1.0 can be found in [9,17,18], however, its architecture is briefly described below to provide a basis for the discussion of the eDOTS 2.0.

The design of the eDOTS 1.0 is made up of three separate layers: Sensor, Middleware, and User Interface. The sensor layer is responsible for providing a software abstraction of the underlying physical sensor in the form of a sensor service. The Middleware layer contains discovery and the filter services that are responsible for locating available sensor services and communication between the sensor services and the user interface. The user interface layer is responsible for providing a graphical interface to the observer (i.e., entity interested in tracking an object of interest) as well as communicating with the middleware layer in order to retrieve data related to the tracking of an object. The design of the eDOTS 2.0 reused some components of the eDOTS 1.0 and enhanced the remaining components. Figure 1 indicates the components that were modified between version 1.0 and 2.0 of the eDOTS and Figure 2 presents the sequence of activities occurring in the eDOTS 2.0. A discussion of various components of eDOTS 2.0 is presented in next few subsections.

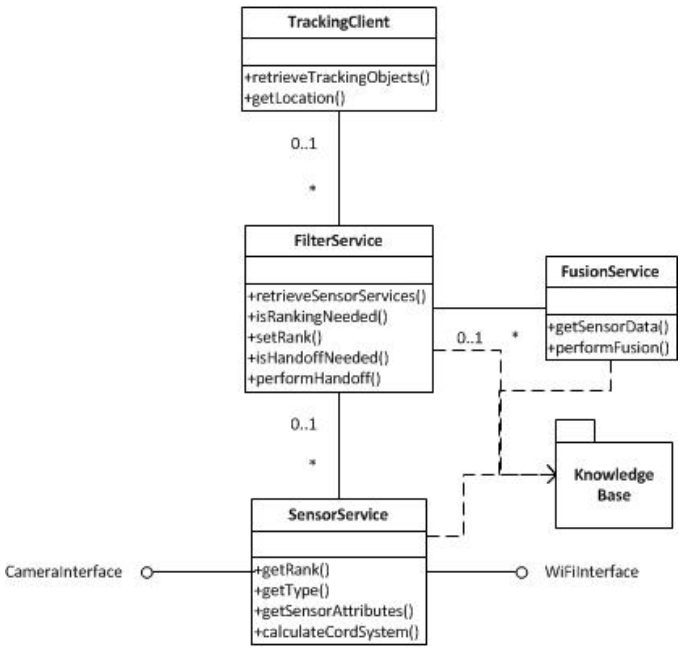

Figure 1. eDOTS 2.0 Enhancements

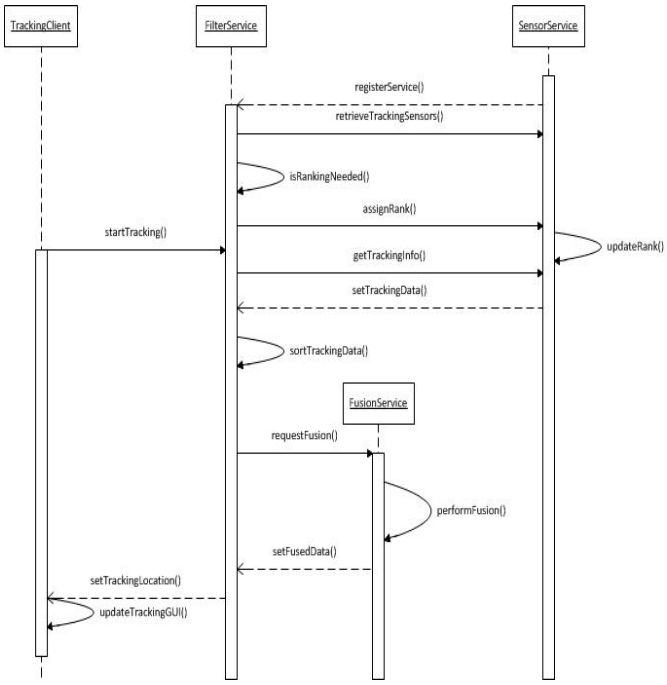

Figure 2. eDOTS 2.0 Tracking Overview

A. *Multi-Sensor Data Fusion*

Data fusion is defined as the process of combining a collection of data results in an effort to present a single representation of the data [21]. This process requires identifying and merging data readings from a set of sensors, within a given time frame, that are currently tracking an object. Unlike the homogeneous sensor situation, the data fusion in a multi-modal scenario has to tackle several formats (e.g., varying degrees of freedom associated with different classes of sensors). The data fusion process in the eDOTS 2.0 begins when the Tracking Client (see Figure 2) issues a request, on behalf of a user, for an object to be tracked. This request is handled by the Filter Service. The Filter Service is responsible for collecting data from various sensors that are able to locate the object, pass this data set to the Fusion Service, and then relay the fused result obtained from the Fusion Service back to the Tracking Client. This combining of data, carried out by the Fusion Service, can either be through simple averaging of the data estimations provided by different sensors or the use of more complex methods such as a Kalman-based technique [5,23]. This result provided to the Tracking Client by the Filter Service is in the form of a tuple representing the X, Y, and Z coordinates of the object and an associated time-stamp. This result then can be graphically displayed to the user.

One implicit challenge in the fusion process is the problem of subset selection – i.e., identifying a subset of sensors out of the ones that are able to track the object at a time instant. Once this subset is selected, the next task is to tackle the heterogeneity (e.g., THE NUMBER OF degrees of freedom) associated with the data readings of the selected sensors. There are many possible approaches to the subset selection problem – three alternatives are described below.

The first alternative is to take all of the data, regardless of the sensor modality, and send it to the Fusion Service. In this approach, the Fusion Service is responsible for deciding an appropriate technique to combine heterogeneous data. The second alternative is to separate the data by the sensor modality type prior to sending it to the Fusion Service. In this method, the Fusion Service can merge the data belonging to each modality separately. This technique allows a comparison between the readings provided by various classes of sensors. This pre-filtering activity is done by the Filter Service. The third alternative is to allow the Filter Service to only send those results that meet a specific Quality of Service (QoS) criterion as set by the Tracking Client. In this situation, the type of sensor modality is not directly examined but rather the selection of the data is based upon the QoS that the particular sensor provides. Similar to the first alternative, in this approach, the Fusion Service is again responsible for identifying a proper technique to merge heterogeneous data. The eDOTS 2.0 uses the third option (i.e., based on the QoS), as many application domains are susceptible to specific quality requirements and various different QoS attributes (e.g., accuracy, lag time, resolution, etc.) of sensors can be specified and used in the fusion process. Also, past experiments with the eDOTS 1.0 have identified the fusion process as the most time-consuming task if such a QoS-based pruning is not performed [17,18].

TABLE I. PARTIAL KNOWLEDGE BASE – SENSOR CLASS RANKING

Sensor Modality	***Rank***
Vision (1)	1
Vision (2)	2
Wi-Fi	3

The eDOTS 2.0 uses a concept of Knowledgebase (KB), shown in Figure 1, for storing information about sensor classes, their dependencies, and the topology of an environment. A starting point for this KB is to identify different classes of sensors that are potentially deployed in each environment. Each of these sensor classes is assigned a rank based on their typical QoS attributes. For example, as shown in Table I, Webcams with higher resolutions are assigned a rank of 1, while the ones with lower resolution are assigned a rank of 2. As the typical accuracy of Wi-Fi sensors is lesser than that of any vision-based sensor, the Wi-Fi class is assigned a rank of 3. Various other classes of sensors (e.g., RFID), when added to the setup, can be assigned different ranks similarly. When a sensor instance is deployed in the indoor setup, it communicates with the Filtering Service by indicating its QoS attributes. The Filtering Service then is responsible for assigning an appropriate membership and hence, a rank for each deployed instance – a simple algorithm, indicated in Figure 3, can be used to assign ranks to various sensor instances. The Filtering Service is also responsible for gathering the physical locations of deployed sensors and augmenting the KB with this information. The Filtering Service can also collect information associated with each sensor instance based on the results received from that instance. It can use this information to dynamically change the sensor class membership and hence,

the rank, of each instance during the life cycle of the eDOTS 2.0.

Sensor Ranking Algorithm (Sensors, Ranking Attribute)

Input: Array of Sensors (A[]) Ranking Attribute (Attr)
Output: Array of Ranked Sensors (A[])

1. Check to see if each *A[i]* in *A* is currently ranked.
    1. If the sensor has not previously been ranked we need to establish a rank of *null*.
    2. Otherwise, continue to Step 2.
2. Check each sensor, *A[i]*, against the providing ranking attribute, *Attr*.
3. Assign a rank based upon the ranking attribute, *Attr*, to each sensor *A[i]*.
    1. If *A[i]* exceeds the *Attr* requirement then assign a rank of *1*.
    2. If *A[i]* meets the *Attr* requirement then assign a rank of *2*.
    3. Otherwise, assign a rank of *3*.
4. Repeat Steps 2 and 3 until all sensors have been ranked.
5. Make note of each sensor ranked and its associated rank in local array *S[]*.
6. Return array of ranked sensors, in ranked order.

Figure 3. Ranking Algorithm

The KB method described above is a simple first-attempt at addressing the issues associated with multi-modal tracking and it is very static. The problems associated with multi-modal tracking include handling of mismatched quality of service properties such as different levels of spatial resolutions, different or mismatched number of degrees of freedom, and different accuracy characteristics. For example, in vision-based trackers, even though the spatial resolution tends to be high, inside-out trackers and outside-in trackers have very different accuracy characteristics. The inside-out trackers (i.e., a moving camera looking at statically placed markers in the tracked space) typically are very accurate in orientation estimation but not so good at location estimation. The outside-in trackers (i.e., multiple cameras statically installed around the tracked space, tracking a moving marker) are, in contrast, very accurate in location estimation of the marker and not very accurate in orientation estimation. Wi-Fi based trackers lack the spatial resolution of vision-based trackers, but can be more pervasive. The challenge then is how to optimally utilize the subset selection and the fusion processes so as to remove the poor performance aspects of the particular trackers and have them complement each other to provide a more accurate estimation of the tracking parameters. In addition, it is desirable to do this in a dynamic fashion. For example, markers may become occluded in the camera views in vision-based trackers in which case, it may be desirable to include less accurate trackers such as Wi-Fi based trackers to bridge the gap. The noise characteristics may also vary with time, in which case, the use of more complex fusion methods such as Kalman filter or particle filter would be more useful [1]. Utilizing machine learning techniques may also help with the dynamic aspect of subset selection [19].

B. Coordinate System Transformations and Handoffs

As any indoor tracking system encompasses sensors that are geographically dispersed, each of these sensors may have entirely different coordinate systems which they are utilizing. For instance, in a typical office building there may be many rooms on each floor. Each room may consist of a sensor that may have an established coordinate system for its own environment. This coordinate system is local to that particular environment and thus, when an object moves from one room to another a handoff and associated transformation must occur between different sensors. To remedy this problem, the eDOTS 2.0 uses the concept of the Spatial Relation Graphs (SRG) as introduced in [16]. An example of when a handoff and coordinate system transformation would be needed is shown in Figure 4.

In addition to the need for handing off, a multi-modal sensor-based setup is prone to an additional overhead when attempting to provide a coordinate system handoff and transformation between the various sensors. This additional overhead is due to the fact that different sensor modalities may have different characteristics, such as different degrees of freedom, and thus, may need specialized adaptation before applying the SRG principles as discussed in [17,18]. An example of a situation in which such adaptation is required would be if an object leaves the vision-based environment and enters an adjacent environment that contains Wi-Fi-based sensors. This handoff is required both due to the difference between the two coordinate systems that each sensor type is using and the physical movement from one environment (such as a room) to another (such as an adjacent room). In the case of the vision-based environment, a single sensor can identify an object's location, whereas in the Wi-Fi environment, three access points are needed to identify an object's position based upon triangulation.

The eDOTS 2.0 borrows the concepts proposed in [17,18] for the purpose of tracking handoff and transformation. In the Wi-Fi and Vision infrastructure, as used in the eDOTS 2.0, the transformation must be adapted for inclusion of the Wi-Fi component. The adaptation involves determining the location of the Wi-Fi access points involved in the tracking process. This information is stored in the KB when the Wi-Fi Service registers itself for tracking. We can then use this information along with the Vision-based information to begin the transformation process. The Wi-Fi component only provides data for the X and Y axis in the tracking environment and thus, the transformation process in this instance only evaluates using these data readings. Since we now know the estimated location of the tracking objects position and the physical location of the various sensors, we can now begin the transformation process as described in [17,18]. This process of adapting to a multi-modal sensor environment brings about the challenges of determining the handoff point and coordinating the transformation. In the eDOTS 2.0 we address these issues by using the highest ranked sensor environment precedence over the lower in determining this handoff point, thus the highest ranked sensor environment will dominate tracking and handoff will only occur when that environment is no longer able to provide tracking estimates. The information and coordinate information used by this higher ranked sensor modality will

then be used by the lower ranked modality to perform the coordinate transformation.

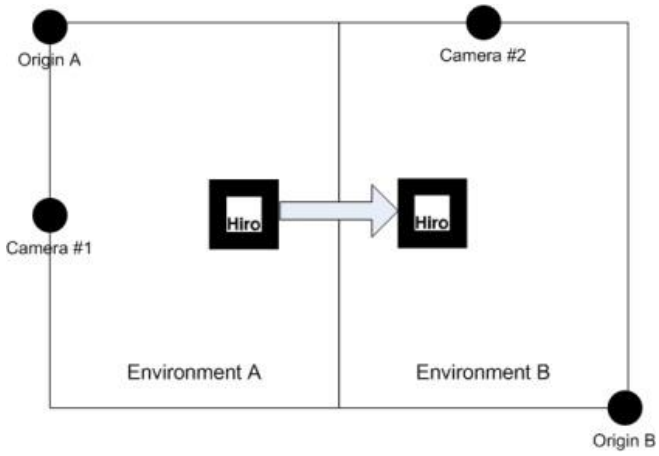

Figure 4. Coordinate Transformation & Handoff Example

III. EXPERIMENTATION

For an empirical validation, the eDOTS 2.0 is deployed in an experimental laboratory setup. The eDOTS 2.0 software is developed and run using the Eclipse IDE running Java 6. The software of the system consists of twenty-five classes and five interfaces. Software patterns were used in eDOTS 2.0 with the Adapter pattern [8] being used for the additional components involved with the Filter Service. JINI is used as the network architecture of the system for communication and discovery. The physical infrastructure includes ten Dell OptiPlex GX620 Pentium 4 machines running Windows XP SP3 with 1 GB of RAM. Each machine has two inexpensive webcams (made by Logitech and Micro Innovations) attached to it – one of the Webcams is of a better quality than the other. Additional equipment includes a HP Pavilion dv9000 Centrino Duo machine running Windows XP SP3 with 2 GB of RAM. These two devices allow for Wi-Fi tracking abilities for the eDOTS 2.0. Finally, the existing wireless infrastructure provided by Indiana University Purdue University Indianapolis (IUPUI) is used for the purpose of Wi-Fi-based tracking. This infrastructure consists of numerous access points mounted throughout the building. Physical measurements were manually taken of the locations of all stationary devices and the Wi-Fi access points. These measurements were then used to compare the accuracy of the results obtained from various experiments. This information was stored in the KB and could be accessed by the various sensors to determine their individual physical location within the setup. As these access points were physically present before the KB was developed, gathering this data and providing it in the KB was carried out as an offline activity. Through the availability of this information, it allowed for all estimations provided by the eDOTS 2.0 to be compared to the actual physical manual measurements.

Two patterns (such as the Hiro pattern shown in Figure 4), and a Wi-Fi enabled device were used as the objects to be tracked throughout the course of various experiments. The two tracking patterns were printed on 8.5 x 11 pieces of white paper and attached to a hard board. These objects were moved through the environment by an individual that entered and moved throughout the tracking environment before exiting. This sample movement was used during our experimentation and the path and types of movement were random.

A. *Experiments Related to Data Fusion In A Multi-Modality Environment*

Earlier fusion-related experiments using the eDOTS 1.0 are described in [9,17,18]. These earlier experiments with the eDOTS 1.0 used only Webcams, while the eDOTS 2.0 experimentation utilized the Webcams along with Wi-Fi sensors.

Experiment 1.1 consisted of moving the Wi-Fi enabled device throughout the lab and the adjoining hallway and tracking it only using the Wi-Fi sensors. This experiment was done over a period of five minutes and was conducted a total of ten different times. Each time the movement of the device was random. The estimated tracking error associated with an object's position when using the Wi-Fi sensors was expected to fall somewhere between 1 and 3 meters. This benchmark was taken from [17,18] with regards to the typical accuracy of current Wi-Fi based location tracking applications. The results from the Experiment 1.1 are shown in Table II. The average error in estimating the position of the tracked object, for both the X and Y axes, is calculated by comparing the physical and estimated positions, determining the error between the two, and then calculating the mean error of the collected data. These error values seem to be consistent with the accuracy of similar systems that provide Wi-Fi only location tracking such as that found in [17,18]. The average time required to compute the location of the tracked object using the Wi-Fi sensors was found to be 16 milliseconds. During the course of tracking the Wi-Fi sensor service interacted with a total of five different access points with three being required to perform the triangulation for the position estimate. In these experiments no data fusion was required since only a single set of tracking estimates were produced.

TABLE II. RESULTS OF EXPERIMENT 1.1 - AVERAGE ERROR (METERS)

X-Axis	***Y-Axis***
1.01	2.02

Experiment 1.2 was conducted to assess the ability of the eDOTS 2.0 to handle multi-modal tracking. As the Wi-Fi sensors only provide 2-dimensional readings, only these were considered while fusing them with the vision-based sensor readings. In this experiment simple averaging fusion was used. Table III shows these results obtained by fusing data from the Wi-Fi and the Vision sensors.

TABLE III. RESULTS OF EXPERIMENT 1.2 - AVERAGE ERROR (METERS)

X-Axis	***Y-Axis***
1.63	1.50

As shown in Table III, the Wi-Fi sensor dominates the overall estimation. This is consistent with the results described in Table II. Experiments 1.1 and 1.2 were both conducted without the invoking the ranking algorithm of the eDOTS 2.0. The overhead of this particular experiment was an additional

33 milliseconds. This overhead takes into account the additional time required to retrieve the Wi-Fi data from the tracking sensor as well the process of pruning and streamlining the tracking data. This overhead was found to be caused in the Filter Service. No additional time overhead was found in the actual fusion process.

The goal of Experiment 1.3 was to evaluate if the accuracy in a multi-sensor environment could be improved through the use of the sensor ranking algorithm, which was described earlier. As there are two different classes of Webcams used in the setup, the better Webcam class (i.e., having a frame rate of 30 frames/sec and 640x480 resolution) was allocated rank 1, while the second Webcam class (i.e., having a frame rate of 15 frames/sec and 320x240 resolution) was allocated the rank 2. As the Wi-Fi class (based on the Experiments 1.1 and 1.2) provided a higher average tracking error than the Webcam class, the Wi-Fi class was given a rank of 3. Since this experiment focused solely on accuracy, timing constraints were not taken into consideration. Table IV shows the results of this experiment. It is evident from these results that the ranking algorithm improves the overall estimation when compared with the results of the Experiment 1.2. Such an observation is evident as the sensor selection process, when using the ranking algorithm, always selects the sensors with the higher rank and then uses their readings in the fusion process. In this specific experiment, the Wi-Fi sensors are not selected for the fusion process due to their lower rank and only the Webcams are selected.

TABLE IV. RESULTS OF EXPERIMENT 1.3 - AVERAGE ERROR (METERS)

X-Axis	*Y-Axis*
0.90	0.93

B. Experiments Related to the Coordinate System Handoff & Transformation

Experiment 2.1 was conducted to assess the coordinate systems handoff and associated transformations provided by the eDOTS 2.0. This handoff process involves switching from one coordinate system to another on the fly with a minimal impact seen by the Tracking Client. For Experiment 2.1, there were two possible avenues to take in order to demonstrate handoff – split the existing sensors in the lab setup into two separate "virtual" environments or to physically move the object outside of the lab to provide two physically different environments.

Initially, the lab setup was "virtually" separated into two different environments by virtue of their coordinate systems as shown in Figure 5. This meant classifying 10 of the Web cameras to be members of Environment #1 and remaining 10 Web cameras to be in Environment #2. This particular test did not include the Wi-Fi sensors in the tracking process.

Using the setup as shown in Figure 5 it was then necessary to begin the tracking process to validate the effectiveness of the eDOTS 2.0 to track an object accurately as it moves from one environment to another.

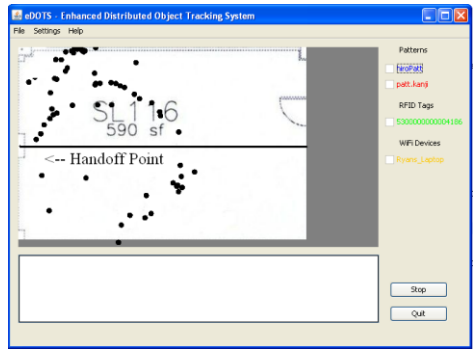

Figure 5. Environmental Setup and Coordinate System Handoff

For Experiment 2.1, the accuracy of the measurements was compared with the physical measurements of the object within the lab setup. A final comparison was done by plotting of the data points using the graphical user interface (GUI) of the eDOTS 2.0 as shown in Figure 5. Figure 5 shows the graphical representation of the object as it moves from one coordinate system to the next. In this experiment, the object was brought into the environment and moved in a circular pattern. This movement caused the object to cross the established boundary between the two coordinate systems, and thus forcing a handoff and transformation between the two coordinate systems. The dots plotted in Figure 5 show the track of the object as it is moved through the environment.

Experiment 2.2 was conducted in order to examine the feasibility of handoff between different classes of sensors. This was achieved by moving from an environment that made use of the vision-based sensors to an environment that made use of the Wi-Fi-based sensors. As a result, we found between 1 and 2 meters of error on both the X and Y axis when conducting this experiment. The results of this test were similar to that found with the Wi-Fi experiments discussed in Experiments 1.1 and 1.2, as the overhead created when transitioning from a more accurate Vision based environment to that of a Wi-Fi based environment is quite high and thus, the accuracy of estimation suffers.

In both experiments, the handoff and transformation from one system to another introduced an additional error while estimating the location of the tracked object. This was often the case from improper sensor readings and the different capabilities of the sensors used in the experimental setup. While improper sensor readings are not specific to a particular sensor modality we found that in the Wi-Fi scenario the use and discovery of various different access points could greatly affect the overall accuracy of the tracking data. In order to examine the accuracy of the handoff process, all of the estimated location data points were compared to their actual measurements. Once the accurate points were identified, the percentage of data points that were within the expected mean error range (as specified in [17,18]) were determined. The results of the handoff test are shown in Table V.

TABLE V. HANDOFF ACCURACY

Total Data Points	*Accurate Data Points*
86	73%

As shown in Table V, the accuracy of the handoff process was such that 73% of the total number of data points was deemed to be accurate estimations of the object's location. Points were determined to be accurate if they fell within the bounds as indicated by the results of the Experiment 1.2. This degree of accuracy, or inaccuracy, may or may not be tolerated based upon the application domain. Therefore, additional work related to the study and improvement of this process is needed.

IV. Related Work

In recent past, many indoor tracking systems have been proposed, both homogenous [1,2,3,10,20,22,24] and heterogeneous [6] in nature. The eDOTS 2.0 differs from these exploratory systems in that it is designed with the goal of effectively tackling heterogeneity between sensor classes. We have also focused on the overall accuracy of the system while attempting to meet real-time constraints of 30 milliseconds. Extensive work has been done in the area of multi-sensor data fusion, such as [21]. In addition to this work, studies have also been conducted on the Federated Kalman Filter and its practical application [3] as it applies to multi-sensor environments. Klinker et al. at the Technical University of Munich have studied ubiquitous tracking in distributed environments [4,11,13,16]. Our work is an extension of this approach, as we have applied these various techniques for the purpose of tracking in an indoor multi-sensor environment. Finally, contributions have been made with respect to using SRG and their application in various different domains [15]. Our work has demonstrated the feasibility and effectiveness of using SRG for the purposes of coordinate system handoffs and associated transformations in multi-modal sensor-based indoor setups. Also, the selection of a subset of sensors, based on an associated rank determined by their QoS attributes, is a novel concept used by the eDOTS 2.0 for the purposes of indoor tracking.

V. Conclusion

This paper has discussed the design, implementation, and experimentation of an indoor tracking system. The contributions of this work are: a) an ability to handle multi-modal sensors, and b) a seamless handoffs and associated transformations. Future work includes an experimentation and analysis using additional sensor modalities, such as the RFID tags and sensors on mobile devices, and investigation of different algorithms for sensor selection and fault tolerance of sensors services.

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