A Data Fusion Model for Location Estimation in Construction

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Abstract

Materials tracking is a key element in a construction materials management system. Deploying a cost-effective, scalable, and easy to implement materials location sensing system in real world construction sites has very recently become technically and economically feasible. The evident drawback of the current cost-effective and scalable systems is lack of accuracy and robustness.

In this research a data fusion model is used on an integrated solution for automated identification and location estimation of construction materials, equipment, and tools. Data fusion is intended to increase confidence, achieve better performance for location estimation, and add robustness to operational performance. The proposed model is a modified functional data fusion model for the application of construction resource location estimation and is based on the US Joint Directors of Laboratories (JDL) model. The paper presents some preliminary and promising results of applying the fusion model on construction field trial data.

Introduction

Material tracking is a key element in a construction materials management system. The unavailability of construction materials at the right place and at the right time has been recognized as having a major negative impact on productivity. Reducing unsuccessful searches for such materials would reduce wasted supervisory time, crew idle time, and disruptions to short interval planning. Conversely, understanding the materials flow over time helps to increase labor productivity, reduce materials stock piles, and reduce materials management manpower.

In an initial attempt to automate materials tracking Caldas et al. (2006) implemented a GPS and hand held GIS based mapping approach that demonstrated some promise for time savings and reduced materials losses under certain conditions. More sophisticated and automated, wireless sensor network based, data collection technologies, using GPS and RFID (Radio Frequency Identification), are being developed for a wide spectrum of applications. Specifically more recent research is demonstrating that coupled with mobile computers, data collection technologies and sensors can provide a cost-effective, scalable, and easy to implement materials location sensing system in real world construction sites (Akinci 2002; Song 2006a; Caldas 2006; Grau 2007, Teizer 2007). The evident drawback of the current cost-effective and scalable systems is lack of accuracy and robustness.

To address these problems, this study incorporates a framework for an integrated solution for automated identification and localization of construction materials, equipment, and tools for large industrial construction projects. A critical element of this framework is the location estimation problem in particular. Therefore, developing a data fusion method for location estimation that is robust to measurement noise while having a reasonable implementation cost would be advantageous. Fusing the different sources of location data is intended to increase confidence, achieve better performance for location estimation, and add robustness to operational performance.

In this framework, a range of simple to complex sensors can be utilized such as RFID transponders, GPS receivers, RFID readers, RFID with GPS chips, ultrasound, infrared and others. It is assumed that a small subset of sensors will have a priori information about their locations. This may happen because they have been coupled with GPS receivers or GPS chips or because they have been installed at some fixed points with known coordinates. This subset is small because no matter how a priori location information is achieved, it is on average one or two magnitudes more expensive per sensor node than estimated location information. For example, many geomatics solutions exist for tracking items accurately and in real time but at a cost that is prohibitive for the problem described here. In addition, even sophisticated and expensive solutions experience multipath, dead space and environmentally related interferences to some extent. Thus, developing a method for location estimation that is robust to measurement noise while having a reasonable implementation cost is a challenge.

This paper is organized in different sections as follows. Data fusion concepts and models are introduced briefly in the next section to provide some background information to the readers. It follows by presenting a data fusion model for location estimation in construction. The field experiments conducted to obtain the experimental data is presented next. The paper provides some preliminary and promising results of applying the fusion model on the construction field trial data.

Background

Data Fusion

Data fusion is a process of combining data or information to estimate the state of an entity. More often, the state of an entity is referred to as a physical state like identity, location, motion over a period of time and others. The human brain can be considered the best example of a data fusion machine.

Functional, process and formal models are three different categories of data fusion models (Steinberg 2001). A functional model can show the primary functions, relevant databases and the interconnectivity among the elements. A functional model does not show a process flow within a system. This means that levels in a functional fusion model should not necessarily perform sequentially. The US Joint Directors of Laboratories (JDL) model is an example of the functional model. Fusion researchers can develop their own models or adopt one of the existing models. Fusion of data results in many quantitative and qualitative benefits.

Building Information Modeling (BIM)

Building Information Modeling (BIM) is an approach to design, construction, and facility management in which a virtual model of a building is constructed digitally. The model contains precise geometry, spatial, and temporal relationships, 3D geographic information, and quantities and properties of building components to support construction, fabrication, and procurement activities and modeling of the building lifecycle (Eastman 2008). BIM can also be integrated with Cost and Schedule Control and Other Management Functions. It can be used to demonstrate the entire building lifecycle including all stages of building, and it is a method for sharing information. It may also ease communication between architects, engineers and construction professionals (Elvin 2007). Usually it is implemented in the form of a standard, and it is related to BrIM (Bridge Information Modeling) and other similar models.

Multi Level Data Fusion Model for Location Estimation in Construction

Model Architecture

Figure 4 describes a modified functional data fusion model for the application of construction resource location estimation. It is based on the JDL model because it is the most widely used system for classifying the data fusion based functions. The first two levels are called low level data fusion and the second two the high level fusion steps and the last level is called a meta-process. In the following figure, the architecture, the data flow and the interrelationships among the fusion levels are illustrated.

The data sources for this model include:

- Different physical sensors
- Different location estimation algorithms
- Context:
    - Received Signal Strength Indicator (RSSI)
    - Positional Dilution Of Precision (PDOP)

- Time
- BIM
  - Georeferenced site map/layout and Drawings
  - Georeferenced 3D models
  - Environmental conditions
  - Schedule (not in the scope of this study)
  - As-builts (not in the scope of this study)
  - Procurement details (not in the scope of this study)

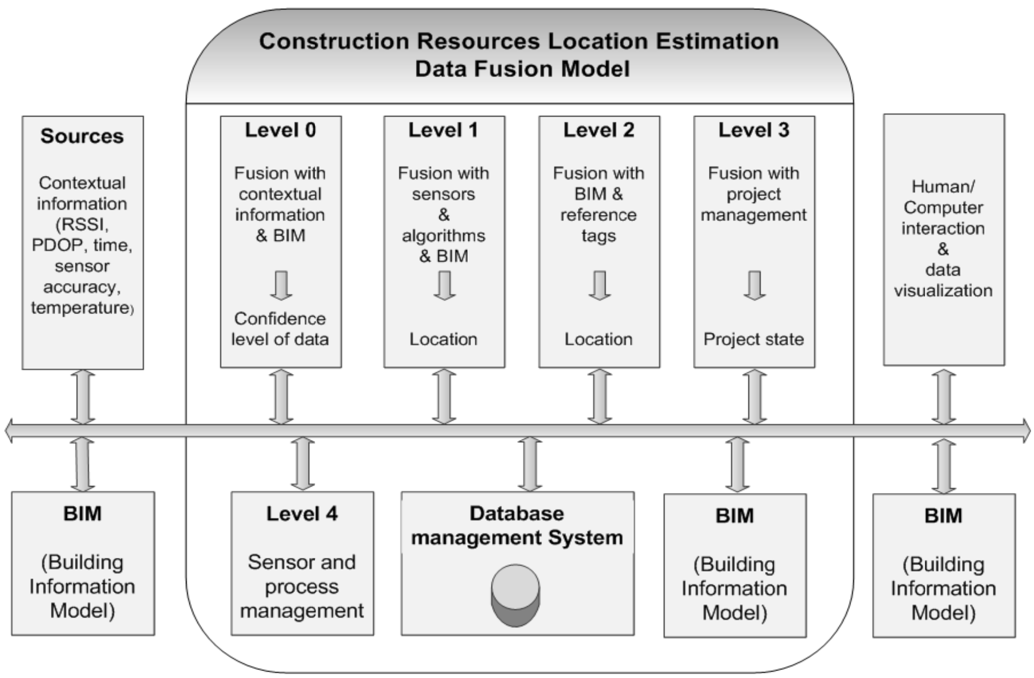

Figure 1: Data fusion model for construction resource location estimation

Data Fusion Level 0

Sensor data reliability assessment is the focus of interest in level 0. In other words, we want the sensor fusion system to utilize a combination mechanism so that the different sensors can "properly" contribute to the "results" in the information space. The "results" means the output of this fusion level and "properly" means with an established confidence, reliability or validity of the information.

Utilizing some location sensing technologies such as RFID, GPS, Ultrasound, infrared, and others gives us some rough location estimations of the materials on site. This very rough estimation is considered as a "read" event or a location observation. In this level, we focus on finding the confidence level of this location observation, based on the reliability and accuracy of the sensors at the time of observation and other layout contextual information that are available or can be adopted from BIM.

Different sensors have different accuracy and reliability factors that differ from each other and there is no simple solution for a proper combination of sensors. Combining the contextual information about the sensors and some other available context about the site layout is a reasonable means to obtain the confidence level of the observed location data. Because some of the context might not be available at all times or for all the sites, using this information is optional in the described solution.

A fuzzy inference system is used for this fusion level, with the ability of employing the contextual data according to their availability. This fuzzy system needs to be re-engineered for any new set of utilized sensors. A thorough description of this fuzzy level 0 fusion is presented in (Razavi 2008) for a scenario of RFID and GPS sensors.

Fuzzy representations and an inference system help to define the observation validity or "trustiness" more precisely. In this regard, observations are not valid or invalid anymore, but they have a degree of trust in the range of valid and invalid (Caron 2004). In other words, the confidence level of the observed location is the output of this fuzzy system that will be used to weight the fusion in the next level of the fusion architecture described here.

Data Fusion Level 1

Level 1 data fusion estimates the location of the construction resource using different reads, sensors, and location sensing algorithms. A fusion of different algorithms to get a more robust estimation can also fit into this level. Site layout and material membership to different site areas can be fused at this level. The Dempster-Shafer theory that is also known as the "theory of belief" or "theory of plausibility" or "evidential theory" is the primary method that has been used in this level.

In the current approach, when an RFID reader reads a tag, the combination of GPS/RFID data gives information about the location of the tag which is a hypothesis. This information can be modeled by a basic belief assignment because of the uncertainty in RFID read range due to the surrounding environment. To deal with this uncertainty, different beliefs are assigned to different subsets of cells centered on the GPS/RFID sensor set such that the sum of the all beliefs are equal to one.

In the simplest scenario, due to environmental and other factors, GPS and RFID are having different reliabilities for each event of "read". Therefore different read events can be considered as the independent observations that can be fused by the Dempster-Shafer theory.

Outputs of the RFID-GPS-based prototype were used as the inputs for the developed Dempster-Shafer-based algorithm in this fusion level. The prototype outputs were estimated locations of the tags, based on the observed read events for each tag. These estimated locations were calculated using centroid model. The following figure illustrates the hierarchical relationship among tag read events, estimated locations of the prototype, and the Dempster-Shafer-based fused estimation (Figure 2).

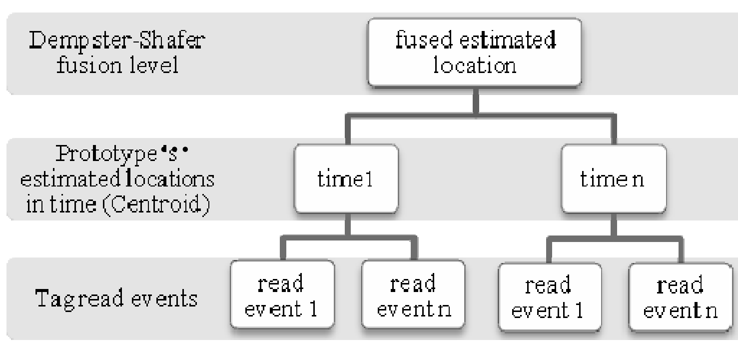

Figure 2: Hierarchical relationship representation among read events, estimated locations, and the estimations of the Dempster-Shafer fusion level

Data Fusion Level 2

It assesses the situation state by integrating the resource location information (Level 1 output) with contextual information, integrated BIM and/or other sensor data –LADAR, ultrasound or 3D Laser Scanner. The relationship between different construction resources and the site layout, as-builts and even schedule can be extracted based on the results of this level. This fusion level can result in a spatial/temporal relationship of elements and the building life cycle.

Fusion Level 2 is situation assessment on the basis of inferred relations among entities. Depending on the different physical and contextual information of the employed construction material locating approach, different solutions and techniques can function in this fusion level. For our approach, landmarks are used to assess the precision and correct the estimated locations of the target tags. The idea of using reference tags as some landmarks to adjust the estimated locations of the target tags is a feasible operation in this level of fusion.

In this framework, a cost-effective, arbitrary set of simple RFID transponders in some fixed and known positions in the construction site is utilized to possibly add accuracy to the estimated locations in the fusion level 1 of our target tags. As the reader agent is roving around and collecting the target tags data and estimating their locations through the level 0 and 1 fusion steps, reference tags data are also being captured at the same time and their locations would be calculated.

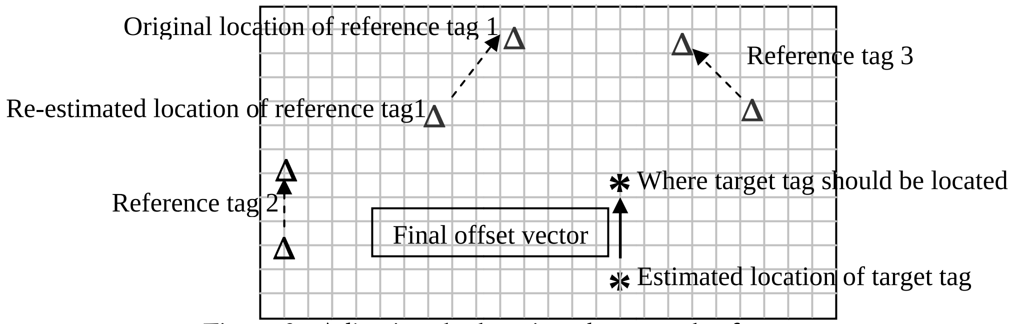

Figure 3: Adjusting the locations by several reference tags

The basic idea is using the vector of difference between pre-defined and re-estimated locations of the reference points and using this vector to offset the newly estimated target tag locations. The accuracy should improve if more than one reference tag can be employed in the framework. The composition of all the reference tags' offset vectors forms the final resultant offset vector (Figure 3).

Data Fusion Levels 3, 4 and Human/Computer Interaction

Level 3 is estimating the project state. This level involves integration with the project management system and is out of the scope of the current work. Level 4 improves the results of the fusion by continuously monitoring and assessing the sensors and the process itself. We may also evaluate the need for additional contextual information or sensors in this level. The need for calibrating the sensors or modifying the process may be assessed in this level. Human/Computer interaction can also be summarized in a data visualization and navigation module as well.

Conducted Field Trials

Field trials were conducted to obtain experimental data to validate the data fusion model and to demonstrate the feasibility of employing the components, methods and technologies developed. A large industrial construction project in Toronto hosted one field trial. An RFID-GPS-based location estimation prototype was used to conduct a comprehensive series of experiments with 375 tags to test the feasibility of tracking and locating some critical components on a construction site and its supply chain.

The data for testing the model are the coordinates of each tag ID on the lay down yards that have been logged on a daily basis for more than five months since the final RFID utilization started on the job site in August 2007. The estimated size of the data set is 100 days of data logging multiplied by average 100 tags on the site per day multiplied by a typical dozen reads per tag per day (Razavi 2008).

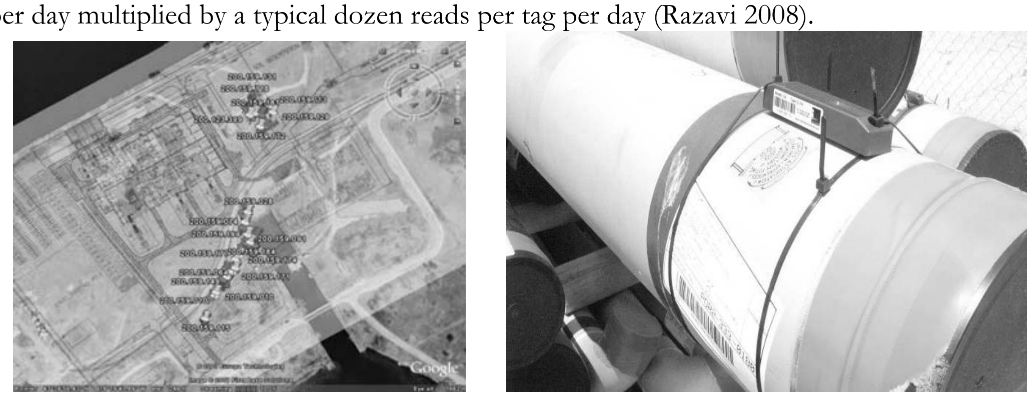

Figure 4: Sample map including some RFID tag location (left), and a sample tagged item (right)

The daily location data is saved in the format of .kml to be opened in the Google Earth map environment for visualizing the location information. An AutoCAD drawing of the site plan that was overlaid on the Google Earth aerial photo provided more landmark reference details for the locations on the site. Maps created in different granularity and various scales to allow proper visualization by field workers. Figure 4 presents a tagged item and a sample map.

Preliminary Results

Data on about 10,000 tag locations is available which represents an average of 100 location estimates for each tag in the field trial period. A case study of a sample data subset – belongs to the site warehouse – is presented in this section. For the subset of data used in this paper, the tags' location data were logged by GPS-enabled readers for 109 tags, three times per day, for four consequent days. The following figure represents the data distribution with respect to the distance between the estimated location – of the prototype based on the reads – and the real location of a tag.

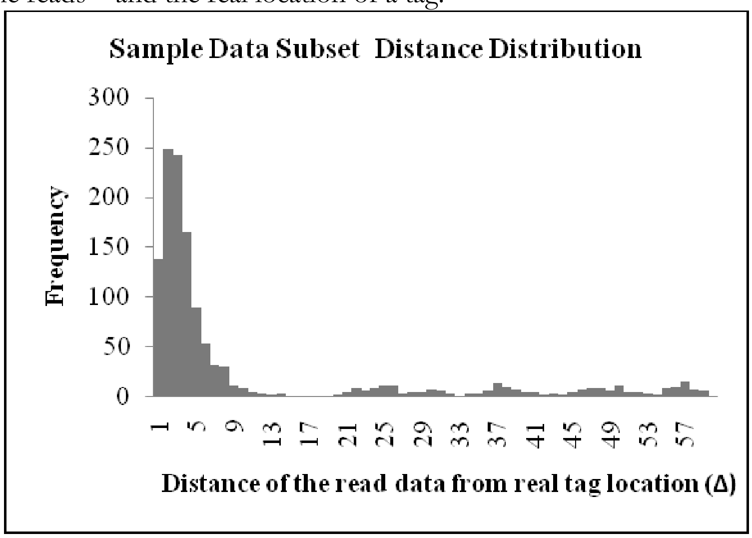

Figure 5: The distribution of the distance for the sample data subset

RFID read rates were sporadic, ranging from ten reads of a tag per minute to periods of hours without reads. Figure 6 presents a case study on how real-time fusion of two algorithms – Dempster Shafer and Centorid- can result in a more accurate estimation of location. In this case study, 8 read events of an RFID tag has been introduced sequentially to the fusion algorithm which represents the fusion level 1 in the implemented model. The final estimated location is equal to the center of the darkest blue area that corresponds to the highest pignistic probability.

Conclusions and Further Research

A functional model was presented for data fusion for location estimation of RFID tagged materials on a construction project. A fusion of two sensors, GPS and RFID, and two algorithms, Dempster-Shafer and Centroid, have been investigated to assess the location for the fusion level 1. Promising preliminary results are presented.

Further results will be reported in the near future. The challenge is to fuse data from simple to complex sensor sources, and contextual information, to estimate object location for tens of thousands of construction objects at an adequate frequency and in a scalable manner. It is expected that integration of fusion levels 0 and 1 will demonstrate significant performance enhancement with respect to measurement noise and will be robust to future advances in technology.

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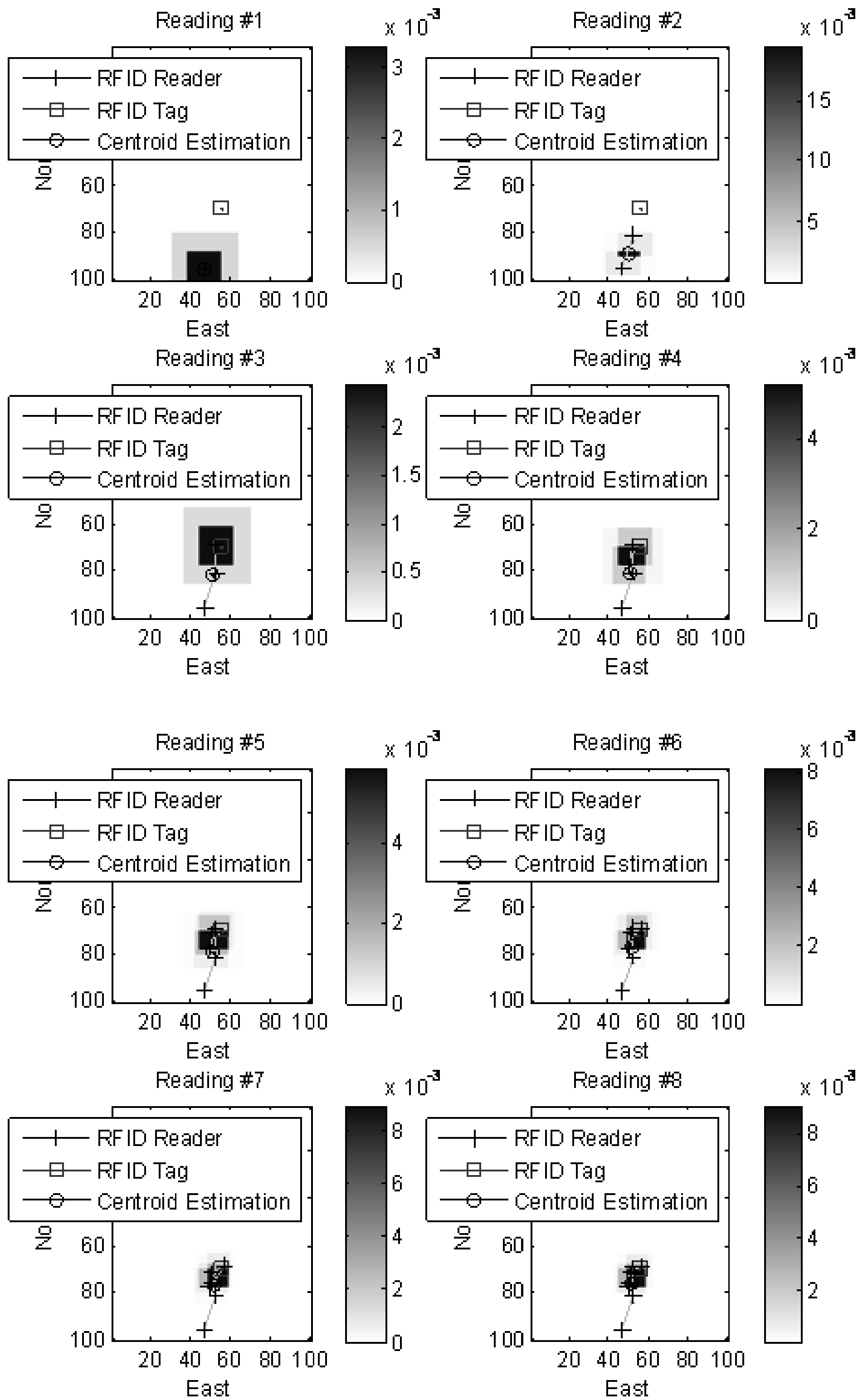

Figure 6: An Illustration on the fused Dempster-Shafer and Centroid methods for RFID tag ID of 200.159.095 after 8 Instances of Reading