Belief Function Based Algorithm for Material Detection and Tracking in Construction

Emmanuel DUFLOS, Philippe VANHEEGHE
LAGIS (UMR CNRS 8146)
Ecole Centrale de Lille
Cité Scientifique
59651 Villeneuve d'Ascq Cedex
FRANCE
Email: (emmanuel.duflos , philippe.vanheeghe)@ec-lille.fr

Saiedeh RAZAVI, Carl HAAS
Department of Civil and Environmental Engineering
University of Waterloo
200 University Avenue
West Waterloo, Ontario
CANADA N2L 3G1
Email: (snavabza@engmail , chaas@civmail).uwaterloo.ca

Abstract—**Dislocation is defined as the change between discrete sequential locations of critical materials such as special valves or fabricated items, on a large construction project. Dislocations of construction materials on large sites represent critical state changes. Detecting these dislocations in a noisy information environment where low cost Radio Frequency Identification tags are attached to each piece of material, and the material is moved sometimes only a few meters, is the main focus of this study. We propose in this paper a method based on the Transferable Belief Model (TBM) to estimate materials locations and detect dislocations. This method has been implemented and real experiments were carried out. The results of these experiments show the ability of the proposed method to track the materials.**

Keywords: Dislocation Detection, Dislocation Tracking, Belief Functions, Sensors Network, Construction Materials, RFID, GPS

I. 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 construction productivity. Moreover, poor site materials management potentially delays construction activities, and thus threatens project completion dates and stands to raise total installed costs [1]. While automated controls are often established for engineered and other critical materials during the design and procurement stages of large industrial projects, on-site control practices are still based on necessarily fallible direct human observation, manual data entry, and adherence to processes. These are inadequate for overcoming the dynamic and unpredictable nature of construction sites. Node location approaches using signal strength and based on triangulation or relaxation algorithms [2]–[4] are limited because of the cost of required node electronics (no current high volume demand exists), and because the anisotropic, dynamic transmission space on a construction site, for example, can not feasibly be mapped at the temporal or spatial resolution required. In addition, even sophisticated and expensive solutions experience multipath, dead space, and environmentally-related interference to some extent. For example, the Wi-Fi RTLS (real time location systems), such as commercial solutions from AeroScout, Ubisense, Ekahau, and the PanGo Network, require extensive calibration to map the Wi-Fi signals to locations throughout a building while the existence of 802.11 access points is not guaranteed for any facility being built. Thus we have selected a more cost-effective approach that is applicable to construction job site specifications. However, developing a method for location estimation that is robust to measurement noise but still has a reasonable implementation cost is a challenge. Wireless sensor network-based data collection technologies such as 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 [1], [5]–[15]. The evident drawback of the current cost-effective and scalable systems is lack of accuracy, precision, and robustness. The study presented here is an improved formulation for robustly processing uncertainty and imprecision in proximity methods. Hence it is naturally developped within the belief function framework and more precisely within the Transferable Belief Model (TBM) proposed by Smets [16]. By proximity we mean a binary spatial-constraint-based method [9]. The approach presented here gracefully manages the issue of dislocated tags, and results are presented graphically in an intuitive format.

For the purpose of this research, an integrated solution for automated identification and localization of construction materials was incorporated for a large industrial construction project. The main focus of the field trial was to develop a data fusion method for location estimation that is robust to measurement noise and has a reasonable implementation cost. The field trial involved a continuous site presence over 16 months by three graduate and three undergraduate students. 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. RFID read rates were sporadic, ranging from ten reads of a tag per minute to periods of hours without reads.

This paper is organized into the following sections. A brief introduction provides background to occupancy cell framework and proximity localization methods. Then, a practical elaboration on formulating belief function theory for locating materials and detecting dislocated items is presented. A brief description of the construction field experiment and the acquired data set follows. The results indicating the potential of the belief function theory to detect materials dislocation make up the next section. Finally, the conclusion summarizes the findings of this research study, and suggests additional further works.

II. Proximity Measure as Localization Process

Proximity as described below first appeared in the reference [17].

A. Localization : Background

In general, there are two approaches to localization. One is fine grained localization using detailed information, and the other is coarse-grained localization using minimal information. The tradeoff between the two approaches is obvious: minimal techniques are easier to implement and more likely to consume fewer resources and incur lower equipment costs, but they provide less accuracy than detailed information techniques. Fine-grained node localization methods are based on specific detailed information and can be categorized into these measurement techniques: Time of Flight Received Signal Strength (RSS) Lateration and Angulation Distance-estimation using time difference (TDoA) Pattern Matching (RADAR) RF sequence decoding. Coarse-grained node localization or connectivity-based localization algorithms are those which do not use any of the measurement techniques described above. In this category, some sensors called anchors have a priori information about their location. The locations of other sensors are estimated based on connectivity information, such as who is within communication range of whom.

B. Introducing Proximity

Proximity is the basis of another localization model that does not attempt to actually measure an object distance from reference points, but rather determines whether an object is near one or more known locations. The presence of an object within a certain range is usually determined by monitoring of physical phenomena with a limited range, e.g., physical contact to a magnetic scanner, or communication connectivity to access points in a wireless cellular network. We suppose here that each material of interest is equipped with a RFID as illustrated in the picture 1 taken from a real construction site.

Some of the proximity-based methods introduced in this section make up a part of the proposed solution for this research. In proximity models, for reduction of computational complexity, a discrete representation in 2D is employed instead of a more realistic continuous model. In the discrete view, a rover (any reader carrier) moves around in a square region, Q, with sides of length s; Q is partitioned into n^2 congruent squares called *cells* of area $(\frac{s}{n})^2$. The RF communication region of a read is modeled as a square centered at the read

Figure 1. Example of a construction site where materials are equipped with RFID

and containing $(2\rho+1)^2$ cells, instead of a disk of radius r. Thus, the position of reads as well as tags is represented by a cell with grid coordinates, rather than a point with Cartesian coordinates, and one is only interested in finding the cell(s) that contains each RFID tag (2). This paradigm is applied in the proximity approaches in particular.

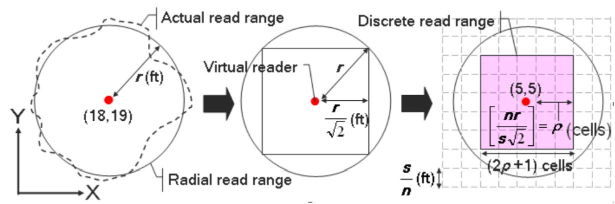

Figure 2. Modelling the Radio Frequency Communication Region under the Occupency Cell Framework [18]

Simic and Sastry presented in [19] a distributed algorithm for locating nodes in a discrete model of a random ad hoc communication network and introduced a bounding model for algorithm complexity. Song et al [18] adapted this discrete framework, based on the concept that a field supervisor or piece of materials handling equipment is equipped with an RFID reader and a GPS receiver, and serves as a *rover* (a platform for effortless reading). The position of the reader at any time is known since the rover is equipped with a GPS receiver, and many reads can be generated by temporal sampling of a single rover moving around the site. If the reader reads an RFID tag fixed at an unknown location, then RF communications connectivity exists between the reader and the tag, contributing exactly one proximity constraint to the problem of estimating the tag location. As the rover comes into communication range with the tag time and time again, more reads form such proximity constraints for the tag. Combining these proximity constraints restricts the feasible region for the unknown position of the tag to the region in which the squares centered at the reads intersect with one another (see figure 3).

Song et al also implemented Simic and Sastrys algorithm in large-scale field experiments ([9]), including as parameters (1) RF power transmitted from an RFID reader, (2) the number of tags placed, (3) patterns of tag placement, and (4) the number of reads generated based on random reader paths. Analyzing

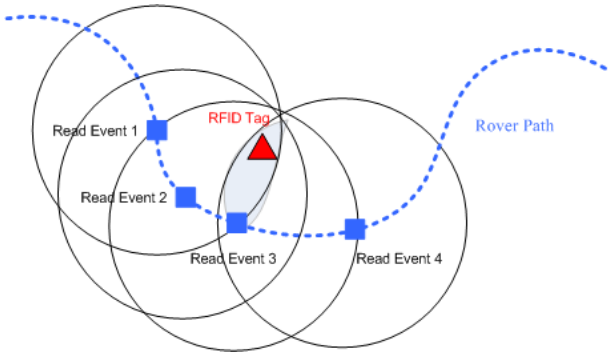

Figure 3. Modelling the Radio Frequency Communication Region under the Occupency Cell Framework

data collected shows that in 51% of the total 4,200 instances, the true location of a tag was expected to be within +/-3 cells from the center of the region estimated to contain that tag. Although this approach was proven adequate (3-4 m accuracy) for static distributions of tags, it is not easily extended to tracking moving or moved tags.

The problem tackled here is the localization of an unknown huge number of communication nodes (the RFID tags) using a moving sensors network. Each node might itself moves and the sensors network is constituted by coupling GPS receivers and RFID readers embended on moving rovers which explore continuously the surface onto which the nodes are disseminated. The raw detections made by the rover may be corrupted by two kind of *errors* :

- When the reader receives a signal from a node, it may only determine a geographic zone within which the tag is located. Hence, a raw detection only provides a inaccurate localization.
- The communication range between a reader and a tag is anisotropic and time-varying : no detection doesn't mean no tag is present in the neighbourhood of the reader. The localization based on raw detections is uncertain.

We therefore need a general framework which modelizes both the inaccuracy and the uncertainty in order to improve both the true detection probability and the localization precision. That is the reason why the Transferable Belief Model (TBM) has been chosen to propose a solution. The TBM framework will not be recalled here but those interested in more readings in that field can refer to the following references [16], [20]).

III. Problem Modeling in the TBM frame

A. The frame of discernment

As a tag can be a priori in any cell of the grid, the following frame of discernment is defined for each tag:

$$E = \{h_{ij} | i = 1, \ldots, n \quad j = 1, \ldots, n\} \tag{1}$$

with h_{ij} the hypothesis: the tag is located in the ith row and the jth column cell of the grid. If the localization was perfect and the communication area was fixe, one would be able, when the reader detects the tag, to determine in a deterministic way a geographic area where the tag is. The imperfections described in the section II-B do not allow the modeling of the knowledge about the presence of a tag in a sure way. It is necessary to split our belief about the presence of a tag on several subsets of cells centered on the localization device.

B. Defining the bbas

As the communication distances are anisotropic and non stationary, it is really difficult to define the subsets related to their preceding description by using only propagation considerations. To cope with these difficulties we have defined these subsets by using some simple geometric shapes like those proposed in the reference [19]. We thus consider for each discrete time a finite suite of square areas B_k centered on the reader, defined by:

$$B_1 \subset B_2 \subset \ldots \subset B_M \tag{2}$$

If the localization device detects a tag at the location (x, y), the set B_k at the same discrete time can be defined for example by:

$$B_k = \{h_{ij} | i \in \{x-k, \ldots, x+k\} \quad j \in \{y-k, \ldots, y+k\}\} \tag{3}$$

The detection of the tag by the localization device means that the tag is in the neighborhood of this one. So, an elementary belief mass is affected to each subsets B_k ($k \in \{1, \ldots, M\}$):

$$\sum_{k=1}^{M} m(B_k) = 1 \tag{4}$$

Figure 4 illustrates this principle for $M = 2$. This kind of belief modeling can be viewed as a very simple solution to take into account the decreasing of the communication signal power.

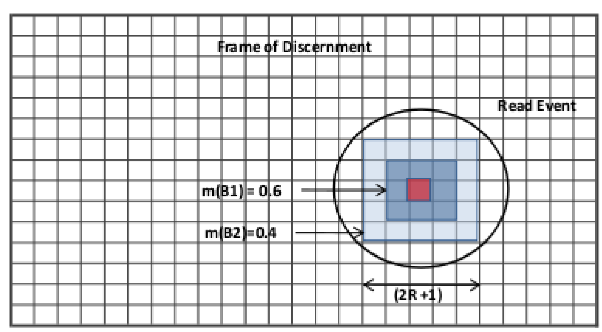

Figure 4. bba modeling for two subsets $B_1 \subset B_2$ of the frame of discernement .

Example 1: Let us assume that the value $M = 2$ is chosen and that the localization device detects a tag at the position (x, y), this position is estimated by using a GPS. The subset

B_1 is defined as $B_1 = \{h_{ij} | i \in \{x-1, \ldots, x+1\} \quad j \in \{y-1, \ldots, y+1\}\}$ and the subset B_2 is defined as $B_2 = \{h_{ij} | i \in \{x-2, \ldots, x+2\} \quad j \in \{y-2, \ldots, y+2\}\}$. For example, one possible choice is $m(B_1) = 0.6$ and $m(B_2) = 0.4$.

The bbas assignation procedure is executed for each discrete time t and for each tag e. For each discrete time and for each tag the bba $m_{e,t}$ is formed, the focal elements of these are the subsets B_k.

C. Fusion of the bbas

As we've just seen, we get at any moment a bba for each tag e. The belief mass at time t is therefore obtained by combining all the previous bbas from time 1 to time t:

$$\begin{aligned} m_{e,1:t}(A) &= (m_{e,1} \cap m_{e,2} \ldots \cap m_{e,t-1} \cap m_{e,t})(A) \\ &= (m_{e,1:t-1} \cap m_{e,t})(A) \\ &= \sum_{A_1 \cap A_2 = A} m_{e,1:t-1}(A_1) m_{e,t}(A_2) \end{aligned} \tag{5}$$

D. Tag Localization : Pignistic Probability Calculation

Once we get the belief function $m_{e,1:t}$ we must decide in which cell the tag is located. We therefore switch to the pignistic level and carry out the pignistic transformation which let us obtain the pignistic probabilities of each hypothesis h_{ij}.

E. Dislocation detection : conflict analysis

The conflict is equal to the empty set belief mass after combination. For the present case, it may have several origins :

- the reader does not work
- the communication zone of the tag is smaller or bigger than the one considered for the initial modelling. The focal elements represent badly the reality and the bba are not well adapted to the problem.
- the tag has moved; the new proximity measure is in conflict with the bba resulting from the previous combinations.

It is supposed here that the readers work well and that the modelling of the communication ranges is realistic. Dislocation is therefore the only origin for a conflict rising and a tag moving may lead to a significant value of the conflict. From an applicative point of view we have to decide which strategy must be carry out when the conflict becomes too high. From a general point of view three strategies are possible:

- After each detection a discounting operation is realized on the last combined bba. This leads to favour the last detection and decrease the weight of the past detections : the older the less significant.
- The size of the focal elements are increased to lower the conflict value.
- If at time t the conflict becomes higher than a given threshold, the detection process is reseted using the bba resulting from the last detection as initialization : $m_{e,1:t}$ is abandonned.

For the sake of simplicity during the implementation stage, the last strategy was chosen.

IV. Algorithmic implementation and issues

In the applications area considered in this paper, n varies from 100 to 1000, so the cells number varies from 10^4 to 10^6. It is possible to estimate that always about ten detection means are moving around on the construction site and each of them makes a reading every second. The application of the belief function theory as described in the preceding sections needs to work on a space which dimension varying from 2^{10^4} to 2^{10^6}. The use of classical matrix algebra is thus impossible in such space. In order to face this problem the method presented in [21] has been used. Each belief mass is caracterized by a set $\{B_k, m(B_k)\}$. Each subset constituted by cells B_k is represented by a binary vector $\{b_i | i = 1..n^2\}$ of n^2 elements, each bit b_i being associated with a cell c_i. The subset of cells B_k is thus depicted by the vector $\{b_i\}$ such that for $i = 1 \ldots n^2$:

$$b_i = \begin{cases} 1 \text{ if } c_i \in B_k \\ 0 \text{ else} \end{cases} \tag{6}$$

By using this representation the intersection of two subsets is obtained by the utilization of the logical operator AND. The parameters of this operator are the binary vectors which represent the subsets. Therefore, the fusion operation corresponds to an element by element product of the matrices (which represent the focal subsets) and the vectors (which represent the masses assigned to each subset of each structure).

V. On-site Implementation and Experiments

Simulations results have been presented in the paper [22] and a first implementation on real data was presented in the paper [17]. In this last implementation data were collected on a real construction site but the dislocations were simulated. In this paper we are presenting results from a second implementation with less materials but where the dislocations are real. The way of implementing the fusion process is the same as the one described in [17]. The experiment was conducted in a parking lot on the University of Waterloo campus with 38 RFID tags. The tags were deployed into separate blocks to provide spatial information for the site plan. These blocks are represented as white squares in the figure 5. This spatial information can be used to easily identify blocks that contained tags and ones that did not. Tag locations were logged through a specified number of runs of the program for a variety of rover paths.

Using these data ROC curves have been drawn for different values of the nested bba. As in example 1 we choose $M = 2$. We've drawn three different ROC curves for three different values of the inside focal element side length l_i (also called the read range). The ratio between the two focal elements is also different :

1) $l_i = 4m$, ratio 1 to 2
2) $l_i = 6m$, ratio 1 to 3
3) $l_i = 8m$, ratio 1 to 4

The corresponding curves are drawn in figure 6.

Figure 5. Tags Location on the Parking Lot of the University of Waterloo. Tags Are Deployed into the White Squares called here blocks. Yellow Points Represent Tag Location as Measured by a GPS.

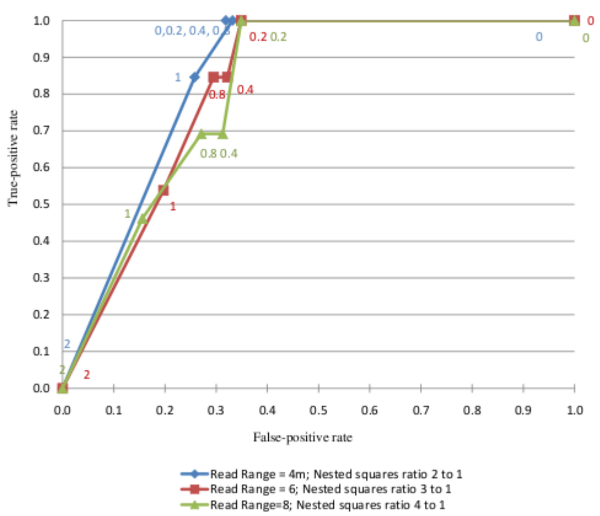

Figure 6. ROC curves for different values of the bba and different ratio between the focal elements

As it can be seen in this figure the choice of the side length of the focal elements is important as it changes significantly the ROC curve mainly in the interval $[0.2, 0.3]$ of the false positive rate (*i.e.* false alarm rate). For instance, for a 0.3 false alarm rate, the true positive rate (*i.e.* true detection rate) is equal to one for $l_i = 4m$ and a ratio 1 to 2 whereas it is only equal to 0.7 and 0.85 in the two other cases. We have also plotted ROC curves for the same value of l_i but for the same ratio for all l_i: 2 to 1. The corresponding curves are drawn in the figure 7. The analysis of these curves shows the importance of the ratio between the two nested squares since this time $l_i = 6m$ leads to the best results in the range $[0.25, 0.3]$ of the false alarm rate. We still need to work on these results to well understand the underlying phenomenon. It is also clear that when l_i is too large, the results become bad. This is due to the fact that the effective (on site) read range is usually lower than $5m$.

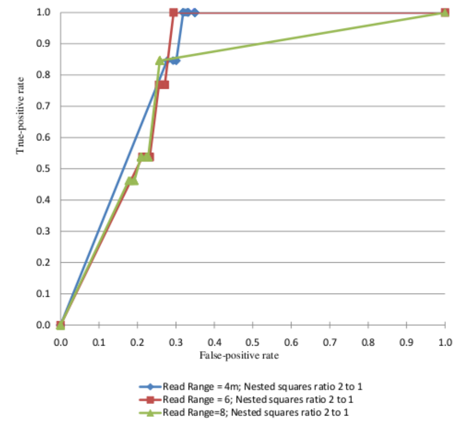

Figure 7. ROC curves for different values of the bba and the same ratio between the focal elements (2 to 1)

The performances of the proposed method are also compared with the performance of a simple threshold on the distance: the thresholding was applied to the distance between the new observation and the average of the previous observations. If the new observation in beyond the threshold distance, it was considered as a dislocation event and the old location information was discarded. The corresponding ROC curve is plotted in figure 8. The main differences are observed within the interval $[0.2, 0.4]$ of the false positive rate. For a 0.3 false alarm rate, the true positive rate is equal to one for $l_i = 4m$ and a ratio 1 to 2 whereas it is only equal to 0.85 in the "distance only" based method. The ROC curve of the Dempster Shafer based method exhibits better performances within the interval $[0.2, 0.4]$ when, of course, the bbas modelize efficiently the reality. This point is important because the improvement is localized in the low false alarm rate section, where we usually want to maximize the true detection rate.

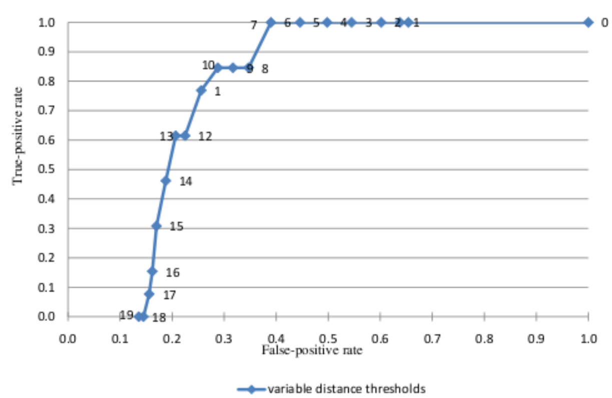

Figure 8. ROC curves for different values of the bba and different ratio between the focal elements

However, as it can be seen on both figures 6 and 8 the true detection rate is still bad within the interval $[0, 0.2]$. More work must be still be done to improve the method in this section since an good operationnal functionning point would be a detection rate near one for a false alarm rate around 0.1.

VI. Conclusion

The targeted application described in this paper is to detect dislocation of materials on a construction site. Each material to detect is equipped with a RFID tag. A rover equipped with a RFID receiver and a GPS receiver is moving on the construction. The RFID receiver allows detections and the GPS localizations. Imprecision and uncertainty are the two main characteristics of this process. The Transferable Belief Model (TBM) is therefore well adapted to propose a solution to improve the detection especially in case of dislocation. We propose in this paper a dislocation detection strategy based on the TBM and on the use of the conflict resulting from successive combinations. In order to do so the space is discretized in a finite but huge number of elementary squared surfaces each of them might contain a tag. All these elementary cells constitute the frame of discernement. After a raw detection by a receiver basic belief masses are assigned to few nested subsets of the space. Each detection is followed by a fusion step with the previous bbas. The conflict is then analyzed and if it is greater than a given threshold, a dislocation is detected. This is not the only way, nor of course the optimal way, to deal with the increasing of the conflict but is is quite simple to manage on a huge construction site. We will come again on this point at the end of this conclusion.

This method has been implemented and evaluated during experimentations. In [17] the data were collected on a real construction site but the dislocations were simulated. In this paper we present experimentations results for less RFID tags but with real dislocations. It is shown here that the belief function based method proposed exhibits better performances than a classical method based on a simple distance thresholding method often used in such applications. This result is only true when the belief functions modelize correctly the RFID read region and the ROC curves are very sensitive to this: the improvement no longer exist with small deviation of the good parameters. More work must still be done to propose a robuts method of detection and tracking of the dislocations.

Moreover, as it can be seen on both figures 6 and 8 the true detection rate is still bad within the interval $[0, 0.2]$. More work must be still be done to improve the method in this section since an good operationnal functionning point would be a detection rate near one for a false alarm rate around 0.1.

It exists today several way of investigations to improve the method. The first one is the way of managing the conflict. It is here very simple but surely not optimal. Moreover, the detection of dislocation is only based on the analysis of the conflict, is it really the better parameter (or at least the only one) for this purpose ?

VII. Acknowledgement

The author would like to thank warmly, François Caron, today researcher at the INRIA of Bordeaux Sud-Ouest (France) for its early but important contribution to the project. The method implemented here are for a large part based on his past work.

References

[1] D. Grau and C. Caldas, "Field experiments of an automated materials identification and localization model," in *Proceedings of the 2007 ASCE International Workshop on Computing in Civil Engineering*, 2007, pp. 689–696.

[2] S. Boyd L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[3] N. Bulusu J. Heidemann D. Estrin, "GPS-less low-cost outdoor localization for very small devices," *IEEE Transaction on Personnal Communications*, vol. 7, no. 5, pp. 28–34, 2000.

[4] L. Doherty L. Ghaoui, "Convex position estimation in wireless sensor network," in *Proceedings of IEEE INFOCOM*, 2001, pp. 1655–1663.

[5] B. Akinci, M. Patton, and E. Ergen, "Utilizing radio frequency identification on precast concrete components - supplier's perspective," in *Proceedings of the 19th International Symposium on Automation and Robotics in Construction*, Sep. 2002, pp. 381–386.

[6] C. Caldas, D. Grau, and C. Haas, "Using global positionning systems to improve materials locating processes on industrial projects," *Journal of Construction Engineering and Management*, vol. 132, no. 7, pp. 741–749, 2006.

[7] S. Razavi, D. Young, H. Nasir, C. Haas, and C. Caldas, "Field trial of automated material tracking in construction," in *Proceedings of the CSCE 2008 Conference*, Canada, Jun. 2008.

[8] J. Song, C. Haas, and C. Caldas, "Tracking the location of materials on construction job sites," *Journal of Construction Engineering and Management*, vol. 132, no. 9, pp. 911–918, 2006.

[9] ——, "A proximity-based method for locating rfid tagged objects," *Special Issue of Journal of Advanced Engineering Informatics on RFID Applications in Engineering*, 2006.

[10] I. Tommelein, "Pull-driven scheduling for pipe-spool installation : Simulation of a lean construction technique," *J. Constr. Engrg. manag.*, vol. 124, no. 4, pp. 279–288, 1998.

[11] F. Peyret R. Tasky, "Asphalt quality parameters traceability using electronics tags and GPS," in *Proceedings of ISARC'02 - Washington DC*, 2002, pp. 155–160.

[12] D. Kini, "Materials management : the key to successful project management," *J. of Mgmt in Engrg.*, vol. 15, no. 1, pp. 30–34, 1999.

[13] E. Jaselskis El-Misalami, "Implementating radio frequency identification in the construction process," *J. of Mgmt in Engrg.*, vol. 129, no. 6, pp. 680–688, 2003.

[14] M. Vorster G. Lucko, "Construction technology needs assessment update," Construction Industry Institute, Austin, Texas, Tech. Rep. Report 173-11, 2002.

[15] R. Sacks R. Navon E. Goldschmidt, "Building project model support for automated labor monitoring," *J. of Computing in Civil Engrg*, vol. 17, no. 1, pp. 19–27, 2003.

[16] P. Smets R. Kennes, "The transferable belief model," *Atificial Intelligence*, no. 66, pp. 191–234, 1994.

[17] S. Razavi, C. Haas, P. Vanheeghe, and E. Duflos, "Dempster-schafer method to detect dislocation of materials in constructions," in *Proceeding of the 12th Conference on Information Fusion FUSION 2009*, Jul. 2009.

[18] J. Song, C. Haas, C. Caldas, and K. Liapi, "Locating materials on construction sites using proximity techniques," in *Proceedings of the ASCE Construction Research Congress*, USA, 2005.

[19] S. Simic S. Sastry, "Distributed localization in wireless adhoc networks," Department of Electrical Engineering and Computer Science, University of California, Berkeley - CA, Tech. Rep. UCB/ERL M02/26, 2002. [Online]. Available: http://robotics.eecs.berkeley.edu/~sismic/PDF/localization.pdf

[20] P. Smets, "Data fusion in the transferable belief model," in *Proceedings of the 3rd International Conference on Information Fusion*, 2000, pp. 21–33, paris, France.

[21] R. Haenni N. Lehmann, "Implementing belief function computations," *International Journal of Intelligent Systems*, no. 18, pp. 31–49, 2003.

[22] F. Caron, S.N. Razavi, J. Song, P. Vanheeghe, E. Duflos, C. Caldas, and C. Haas, "Locating sensor nodes on construction projects," *Autonomous Robots*, vol. 22, no. 3, pp. 255–263, 2007.