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REAL TIME LOCATION SYSTEM IN SUPPORT OF BAYESIAN NETWORK

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ABSTRACT

Location systems are used to track items along manufacturing process. However, the considerable cost from installation and maintenance of the location systems is an obstacle to install the location information system. This research presented a real time location system to overcome the high cost issue. The system is a combination of current location system and complementary mathematical model. The mathematical supporting model based on Bayesian network consists of modified depth first-search algorithm, probabilistic inference algorithm, and priority assigning algorithm. Verification of the system is executed through simulated manufacturing system.

1 INTRODUCTION

Our focus is on improving the performance of RFID based real time Location Information System(LIS). Lampe et al. (2003) discussed the potentials of RFID for movable assets management. Radio frequency technology for manufacturing and logistics control was introduced by Keskilammi, Sydanheimo and Kivikoski's (2003) work of improving system performance analyzing the effects of antenna parameters on operational distance.

Implementing LIS generates several constraints to company's financial capacity. Even though the LIS technology advanced in a fast pace, still high LIS price requires vast amount of investment which prohibits implementing LIS for tracking cheap products and assets. The expensive RFID reader becomes the obstacle for LIS implementation. For example, the excessive cost for LIS installation for either a widely open logistics center or a building with a large number of corridors and offices is why the corporations hesitate in installing LIS.

The main research topics of LIS and asset management system have been focused on improving the hardware performance of system itself. Various research efforts have been conducted for RFID based asset management system and LIS, however, the efforts that handle the practical problem of high installation and operating LIS costs are scarce. An economical and efficient LIS is proposed to overcome the problem of high cost issue. The proposed system can save time and the cost of managing location information of assets.

Section 2 describes the main concept of Bayesian networks and LIS. Section 3 focuses on explaining the concept, structure and algorithm of a new proposed system. Section 4 verifies the validity of the proposed system via applying it to a simulated manufacturing system. Lastly, section 5 concludes the proposal and presents future topics.

2 REVIEW OF BASIC CONCEPTS

2.1 Bayesian Network

A Bayesian network is a probabilistic graphical model that relates a set of random variables and their conditional independencies via a directed acyclic graph (DAG). The nodes represent random variables in Bayesian sense; the unconnected nodes are conditionally independent of each other.

Consider a Bayesian network for a set of random variable $X = \{X_1, X_2, \dots, X_n\}$. The network X consists of network structure S which represents the conditional independence relationship among the variable and the set of probability distribution P, these S and P decide the joint probability distribution of X. The structure S is DAG and has a 1-to-1 mapping relation with variable set X. Let X_i be a node of network, Pa_i be the parent node of each node. All the nodes not connected to each other are conditionally independent. Then the joint pdf of X can be written as equation (1).

$$p(X) = \prod_{i=1}^{n} p(X_i | Pa_i) \quad (1)$$

The exact inference of Bayesian network is known to be an NP-hard problem. Approximation methods using Monte Carlo simulation also have NP-hard complexity. Some efficient algorithms exist to solve the exact inference in restricted classes of networks. In general, estimating inference for Bayesian networks with many nodes is intractable. Thus, developing heuristic algorithm is the general approach to estimate inference.

2.2 Real Time Location System

2.2.1 Basic Concept

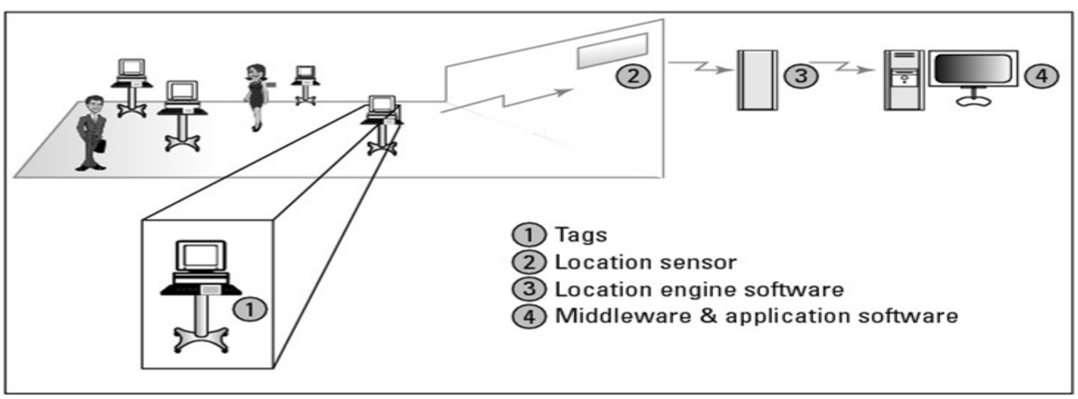

Figure 1: Basic elements of real time location system (Malcik 2009)

Real time location system uses location information of assets to identify, track, control, analyze and manage. Real time LIS attaches or imbeds inexpensive tags into assets to identify and track. Figure 1 explains the basic elements of a real time location system consisting tags, location sensor, location engine and software.

Tag is a small device for location identification. Location sensor, which has specific location information, traces tags. Location engine decides the location of tags by exchanging information with location sensor, and then reports the tag's location to middleware and software. Middleware, which is a software for real time LIS elements (tag, location sensor, location engine), provides information to software which controls the whole system. Software is the IT system to implementing LIS, exchanging information with middleware, the backbone of the system. These elements can be distributed into multiple systems. The basic characteristics of real time location system are application area, response speed and the accuracy which is used for classification standard. Existing real time LIS is classified into two ways; point based and location based. Figure 2 shows two categories of LIS.

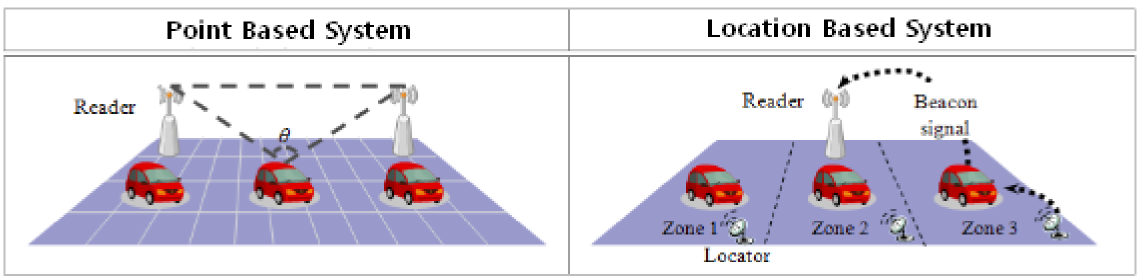

Figure 2: Point based system and location based system

The point based system, the most expensive LIS, is consisted of multiple sensors and tags. It uses three dimensional coordinates to identify the very accurate location of objects and report the location of the objects in three dimensional coordination.

The location based system is less expensive one compared to point based, consisting of locater which identifies location of objects and beacon signal which sends information to a reader. It reports the location of the objects in a rough way compare to point based (for example, "the object is in zone 2").

3 ALTERNATIVE REAL TIME LOCATION SYSTEM

3.1 Proposal of Alternative System

The proposed system in this paper is partially substituting existing LIS with a mathematical one. It still maintains the concept of existing LIS, however it handles the issues of high expenditure for implementing and operating LIS by mathematical models.

The goal of proposed system is to achieve the economical efficiency, so it can be used practically in a real situation. In the proposed system, we adopt the concept of location based system, and a Bayesian network for the mathematical model's reference to overcome the issues of high expenditure of implementing and operating LIS. In a nutshell, the proposed system is an integration of classical real time LIS and probabilistic real time LIS.

3.2 Framework of Alternative System

Figure 3 shows framework of the proposed system. Location based real time LIS, Bayesian network, and integration system are the three subsystems of the proposed system. Location based system covers the area where RFID based LIS is installed, and the Bayesian network controls the location information probabilistically via mathematical model for non RFID area (NRA). Integration system is the backbone of the proposed system whose role is exchanging information between location based LIS and Bayesian network.

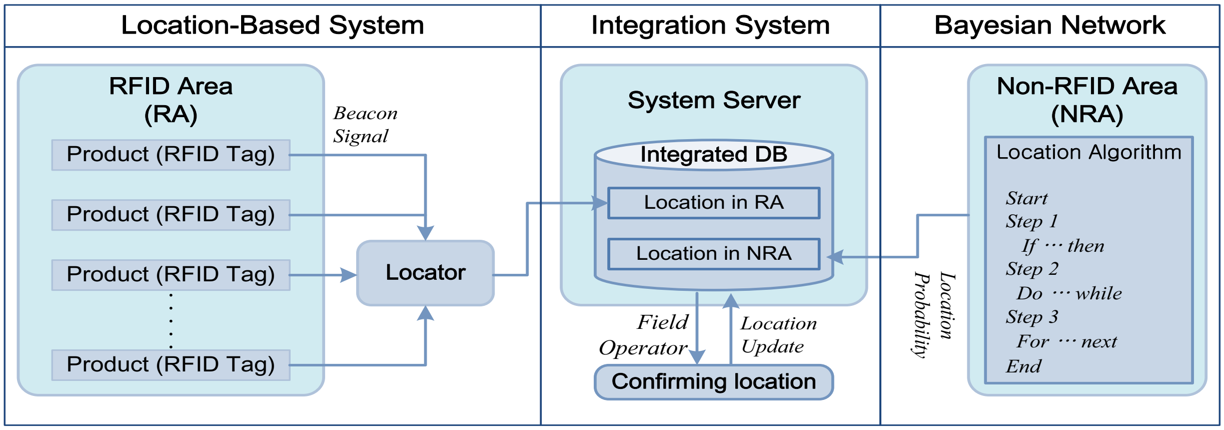

Figure 3: Framework of alternative system

All the objects that transit through location based LIS area have RFID tags. Each object sends beacon signal through RFID tag that will be stored and managed in integration system. Bayesian network, containing an algorithm for location inference, covers NRA. Estimated location information by algorithm is also stored and managed in integration system.

Consequently, the role of integration system is managing the object's location information, via storing and combining, from RFID installed area and Bayesian network of NRA efficiently and accurately. However, we need a process to verify the real location of the objects due to the probabilistic nature of the object's location information from NRA. To guarantee this, we need close contact with operators at the NRA area. We also need to update the verified location information fast and accurately.

3.3 Algorithms for Inferring Location

The location estimating algorithm at NRA starts when the beacon signal from an object's tag is not reported for certain amount of time. Absence of beacon signal for fixed amount of time implies the object left the RFID area for NRA area.

Objects that moved to NRA area carried location reporting history from RFID area since it passed the RFID installed area. The location estimating algorithm at NRA area starts from the object's last position of RFID area, since the last position affects and decides location changes in NRA area significantly.

Once the last position in RA area is available, LIS for NRA area searches all the possible routes objects can take. The modified depth first search (MDFS) algorithm is used to find all routes. Residing probability is the chances of objects take certain route or reside in a certain node. Calculating residing probability process using probabilistic estimation algorithm for all the possible routes in NRA area is followed. Residing probability for all the possible routes and its status can be obtained by using modified depth first search algorithm and probabilistic estimation algorithm. Residing probability for each status can be obtained by treating residing probability for each route as weights. Prioritizing objects location can be assigned by sorting the residing probability in ascending order.

Figure 4 shows the steps of location inferring algorithm.

3.3.1 Modified Depth First Search Algorithm

Depth first search algorithm is generally used for searching routes in graph; however it is not directly applicable for our situation. Since depth first search algorithm visits the entire node once, it is not possible to reflect all the inflow from parent nodes if a child node has more than two parent nodes. This issue prevents from considering all the possible routes to aggregate residing probability of each status. Modification is needed in depth first search algorithm to make it possible to re-search nodes with more than two inflows. We handle this issue by assigning rank attribute to each node.

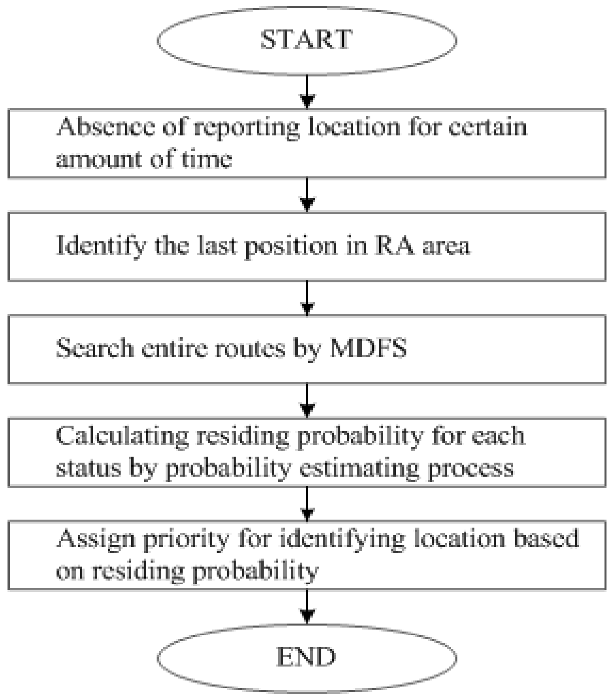

Figure 4. Flow chart of location inferring algorithm

Figure 5 displays a simple graph search example of using modified depth first search algorithm. Route A-B-D searched in (a), node D is initialized again in (b). This initialization enables to search node D again in (d) even node C is searched in (c). Each node has transition probability to child node. Product of each node's transition probability in certain route is residing probability of the route; this will be used as residing probability weights in probability estimation algorithm for a route in next section. Values next to link in Figure 4 represent transition probability from a parent node to a child node. Possible routes are A-B-D and A-C-D, residing probability for each route is $0.6 \times 0.1 = 0.06$ and $0.4 \times 1 = 0.4$, respective-ly.

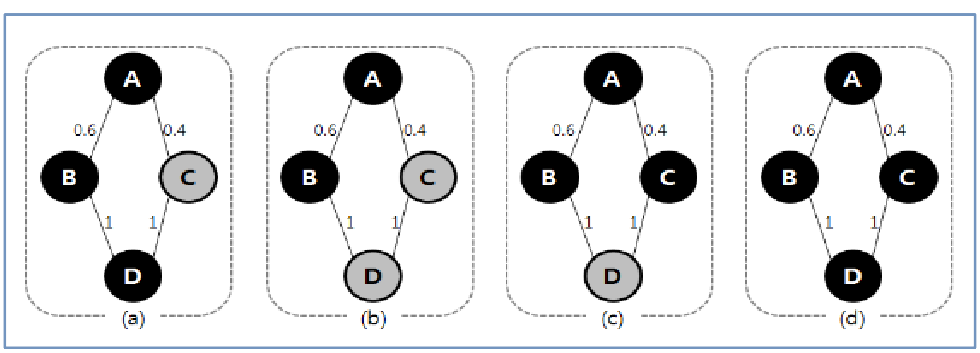

Figure 5: Example of modified depth first search algorithm

3.3.2 Algorithm for Inferring Probability

After modified depth first search algorithm completed searching all the possible routes, then it must calculate residing probability of each node in all routes. Calculating residing probability by probability estimation algorithm is discussed in this section.

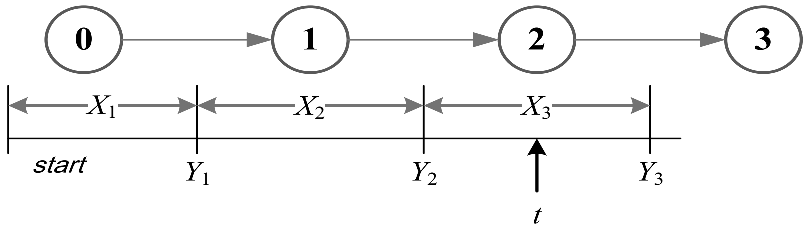

Figure 6: Concept of inferring probability

Figure 6 is a simple graph to explain the probability estimation algorithm. Node 0 is the objects' last position reported in RA area, node 1, node 2, and node 3 are the possible positions that objects can take in the NRA area. Define random variables of Figure 5.

X_i : time stayed in node i
Y_i : time needed to leave node i
L : location of object
t : given time

Equation (2) can be formulated from the definitions.

$$Y_i = \sum_{i<j} X_i \tag{2}$$

From Figure 6, residing probability for each node of all routes can be classified into three cases. The first case is when an object status is movable and resides in the nearest node. For this case, only the upper bound of available area for object next position should be considered. Object should be in node 1 during the given time t for identifying location of an object. Y_1 should be bigger than given time t for an object reside in node 1. Since node 1 is the first one, constraint can be simplified.

If an object status is movable and resides in the furthest node, the lower bound of available area for the object's next position should be considered. Object should be in node 3 during the given time t for identifying location of an object. Y_2 should be less than given time t for an object residing in node 3. Since node 3 is the last one, constraint can be simplified.

For the third case, the lower and upper bound of available area for object next position should be considered. If an object resides in node 2 at time t, t should be bigger than Y_1 and not bigger than Y_2. Thus, residing probability for each node should be calculated using conditional probability.

Above three cases can be written as equation (3).

$$Pr(L=i) = \begin{cases} Pr(Y_i > t) & (for\ min.i) \\ Pr(Y_{i-1} \le t) & (for\ max.i) \\ Pr(Y_i > t | Y_{i-1} \le t)\, Pr(Y_{i-1} \le t) & (o/w) \end{cases} \tag{3}$$

Residing probability for each node of all possible routes can be calculated using equation (3) and will be used by the priority assigning algorithm in next section.

3.3.3 Algorithm for Determining Priority

Final residing probability for each node should be calculated with all the possible routes available and residing probability of each route and node. Total residing probability for each node is the sum of residing probability for each node using residing probability for each route as weights. Total residing probability for node i can be calculated as follows. Let L_i be total residing probability for node i, $path_j$ be residing probability for path j, $L_{j,i}$ be residing probability for node i in path j.

$$L_i = path_j \times L_{j,i} \tag{4}$$

Let $\boldsymbol{L}$ be a set of L_i 's from equation (4) and define rank as

$Rank(i)$: node of i^{th} high residing probability.

Prioritizing residing probability is possible as:

$$Rank(1) = \max \boldsymbol{L} \tag{5}$$

$$Rank(i) = \max\{\boldsymbol{L} \,/ Rank(j < i)\} \tag{6}$$

Probabilistic location information of an object can be verified based on above process. Proposed system assigns the location identifying priority with probabilistic location information, and then reports location information based on priority.

4 VERIFICATION

4.1 Experimental Design

We applied our proposed system to a simulated manufacturing system which is simplified as a graph in Figure 7. The simulated manufacturing system has twelve processes. Process 1 is the obligatory one and the rest eleven processes are complementary repairing processes. Since our proposed system starts with the known position of obligatory process, assume that the process 1 as the last position of the obligatory process.

Numbers in node represent process in Figure 7. For example, node 1 implies process 1. Values next to link mean probability of representing the case of child node is true if parent node is true. Assume zero for the probability of connecting to a false child node if parent node is true. To guarantee the random duration of time spent at a node, exponential distribution with the parameter as node number times 0.05 is used; that is, pdf of node 2 is defined by $f(x) = 0.1e^{-0.1x}$.

4.2 Application and Results

Assume process 1 is the last position of obligatory process as we discussed previously. All paths originating from node 1 are searched and residing probability for each path using transition probabilities between nodes is calculated. All paths and residing probabilities at time $\boldsymbol{t} = \mathbf{5}$ are in two left columns of Table 1.

Next step is calculating object's residing probability for each path and node. The calculated results are in two middle columns of Table 1.

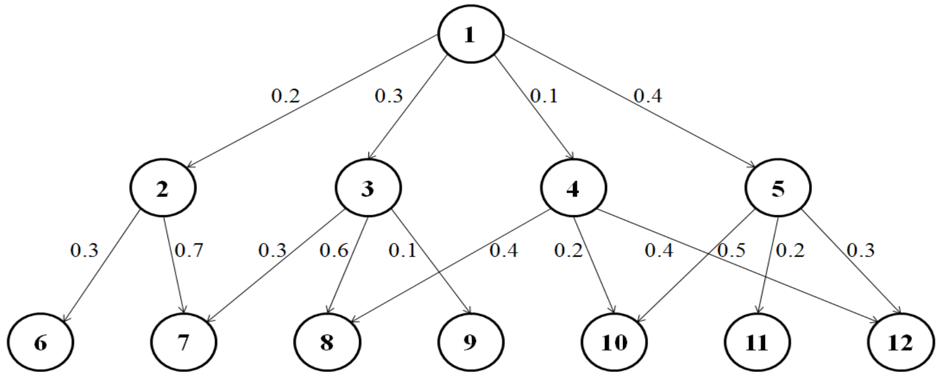

Figure 7: Graph generated by virtual manufacturing system

Table 1: First results of applying alternative system at ***t* = 5**

path	*path probability* (*a*)	*node probability*		*node prob. based on path prob.*	
		2nd node (*b*)	*3rd node* (*c*)	*a*b*	*a*c*
1-2-6	0.06	0.6065	0.3935	0.0364	0.0236
1-2-7	0.14	0.6065	0.3935	0.0849	0.0551
1-3-7	0.09	0.4724	0.5276	0.0425	0.0475
1-3-8	0.18	0.4724	0.5276	0.0850	0.0950
1-3-9	0.03	0.4724	0.5276	0.0142	0.0158
1-4-8	0.04	0.3679	0.6321	0.0147	0.0253
1-4-10	0.02	0.3679	0.6321	0.0074	0.0126
1-4-12	0.04	0.3679	0.6321	0.0147	0.0253
1-5-10	0.20	0.2865	0.7135	0.0573	0.1427
1-5-11	0.08	0.2865	0.7135	0.0229	0.0571
1-5-12	0.12	0.2865	0.7135	0.0344	0.0856

Third step is calculating residing probability for each node by treating residing probability of each path as weights then sum up for each node. Residing probabilities of each path are two right columns of Table 1. Aggregating these two columns generates residing probabilities for each node which is in the node probability column of Table 2.

The final step is to assign searching priority for each node based on object's residing probability for each node. The results are shown in *rank* column in Table 2. In Table 2, the first column of *residing probability* is simulation result with 10,000,000 independent replication, and the second is result with our method. In the third column, *r. e.* means relative error of our result based on simulation result.

5 CONCLUSION

An economical and efficient alternative LIS is presented to solve address the high implementation and operating expenditure of LIS. Proposed system is a probabilistic location estimating system, which is based on Bayesian network. It consists of modified depth first search algorithm, probability estimating algorithm and priority assigning algorithm. It saves cost by partially installed classical LIS. However, the performance is competitive to classical LIS. We tested the performance of proposed system to a simulated manufacturing system.

Table 2: Second results of applying alternative system at ***t* = 5**

node	*residing probability*			*rank*
	simulation	*our method*	*r. e.*	
2	0.1212	0.1213	0.0008	3
3	0.1417	0.1417	0.0000	2
4	0.0368	0.0368	0.0000	9
5	0.1147	0.1146	0.0009	5
6	0.0236	0.0236	0.0000	10
7	0.1025	0.1026	0.0010	7
8	0.1204	0.1203	0.0008	4
9	0.0159	0.0158	0.0063	11
10	0.1553	0.1553	0.0000	1
11	0.0571	0.0571	0.0000	8
12	0.1109	0.1109	0.0000	6

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