

Dynamic Semantic Location Modeling in Mobile Enterprise Applications

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ABSTRACT

A location model represents the inclusive objects and their relationships in a space. This paper presents a framework for dynamic semantic location modeling that is novel at three-fold: (1) Profoundly bring into the enterprise business models the location models (that underlie Location-Based Services - the killer application of M-Commerce). (2) With a novel method of dynamic semantic location modeling, enterprises effectively recognize the needs of the clients and the partners scattering in different locations, advancing existing business relationships if appropriate strategies are exerted. (3) Through the Location Model Platform of information sharing, enterprises are empowered to discover the potential business partners and estimate the values of their cooperation, enhancing their competitive advantages in a market when appropriate partnerships are formed. This proposed framework is implemented with J2EE and gives rise to certain promising evaluation results.

Keywords

Mobile commerce, mobile enterprises, location-based services, location modeling, ontology

1. INTRODUCTION

With the advent of wireless communication technologies, the era of mobile enterprises unfold. Many international enterprises like IBM, Sun, HP and Microsoft are vying to develop mobile enterprise servers and solution architectures. According to a Cutter report, 57% of the employees in the enterprises worldwide will be defined as "mobile workforce" by 2005 [3]. Accordingly, following the e-business trend, competitive advantages built on wireless technologies in dynamic mobile environments are now widely recognized by enterprises.

The quintessence of mobile enterprises is that enterprise users are able to have personalized, seamless access to enterprise applications and services from any place and any time, regardless of the devices employed, in order to make contextualized decisions in behalf of the enterprises [1].

On the other hand, location is an inherent feature of many mobile services. Location-based services (LBS) are information services that exploit knowledge about where an information device user is located. According to Ovum, an analyst and consulting company, the market for LBS will grow to \$12 billion by 2006. However, existing LBS primarily rests on targeted advertising, linking the buyers and sellers more readily and facilitating additional revenue generation [11, 12]. LBS for enterprise decisions are rarely perceived except logistic delivery planning based on geometric models (static location models). The possibilities behind this rareness are two-fold: (1) The integration of enterprise business models and location models is not straightforward. (2) The limitation of existing location models hinders additional developments on enterprise-based LBS.

With the aforementioned suppositions, *this paper aims to present a framework of dynamic semantic location modeling (DSLML) that exemplifies certain integration of enterprise business models and the proposed location model (that surmounts the problems encountered in static location models)*. We anticipate this DSLML framework will trigger myriad research on enterprise-based LBS in the future.

This paper is organized as follows. In Section 2, the limitations of existing location models are addressed. Section 3 then presents the DSLML framework. The preliminary evaluation results are furnished in Section 4. Finally, a conclusion is made in Section 5.

2. Location Modeling

Existing methods for location modeling are two-fold [6]. The first one is geometric modeling that is built upon the geometric coordinate system. The other is symbolic modeling that represents locations with symbols and symbol sets.

Each location modeling method has its pros and cons. Geometric modeling (static location models) has the advantages of high accuracy and easy communication between different kinds of platforms. However, geometric modeling requires reference points and mappings between information objects and geometric coordinate objects. On the other hand, symbolic modeling represents locations with location object names (e.g. 11th Park in Taipei), each of which unfolds as a set containing the objects residing in the designated location. Symbolic modeling accordingly is easy to comprehend, but requires great efforts on managing the naming of the location objects and the handling of the ranges and the overlaps of the location objects [9].

While exerting geometric models (static location models) for enterprise-based LBS, there are two primary problems encountered:

- *Meaningless syntactic information:* A mobile enterprise application system can attain only *syntactic* information objects regarding a given location. For instance, when a salesman queries the system a product sales information for a designated branch office, he may get numerous sales figures for the product at the designated location, but do not know whether these figures imply good sales or bad sales. For situations that salesmen are capable of judging the performance of these figures, the judgments cannot be wisely retained for facilitating subsequent relevant decision making (that might appreciate these *semantic* judgments).
- *No seamless information exchange/integration:* When the exchange or integration of location-sensitive information is intended by enterprises, this might give rise to the need of a middleware for the information translation when enterprises employ different static local models. The rationale is two-fold: (1) The mapping between information objects and coordinate objects in a static location model is fixed (*static*), and thus it is hard to inter-operate the information objects exchanged. (2) This fixed mappings also create difficulties in the merging of the two static location models when tight enterprise relationships are attempted (i.e., the *dynamic* expansion of existing location models).

From the above discussion, there are two vital desired features for enterprise-based LBS: “*semantic*” and “*dynamic*”. “Semantic” indicates that an enterprise can define its own objects, object values, object relationships in a location model [7]. “Dynamic” then denotes that a location model can grow and adapt with the enterprise interactions, building “dynamic links” between locations [4]. These two features drive the necessity of the development in new methods of location modeling in order to shed light on advanced enterprise-based LBS.

DSLML bears these two features in mind and unfolds itself as a new location modeling method. The contributions of DSLML are three-fold (indicated by BOLM, PNLM, and LMP) and described in Table 1. BOLM, PNLM, and LMP differ each other mainly in the scopes of their functions and location coverage.

3. The Framework of DSLML

DSLML aims to fulfill certain integration of enterprise business models and location models in terms of the three DSLML solutions. These solutions involve enterprise clients, enterprise partners, and a platform enabling the search of new partners. Accordingly, interoperability and decision-support aid are the key characteristics of DSLML. This section starts with the description of the ontology employed in DSLML (that achieves interoperability) followed by the three DSLML solutions addressed in Table 1 (that subsequently make decision-support aid realized).

3.1 DSLML Ontology

DSLML fits in the category of symbolic modeling, but the relationships between symbols and symbol sets can be changed dynamically. The DSLML ontology is a shared ontology that is regarded as the interchange format, enabling common access to enterprise operational data [5]. DSLML ontology defines objects,

Table 1. The DSLML solutions for mobile enterprise applications

Solution	Within Enterprise <i>Business-Oriented Location Model (BOLM)</i>	Between Enterprises <i>Partner-Network Location Model (PNLM)</i>	Within Industry <i>Location Model Platform (LMP)</i>
Main Function	Assist an enterprise to understand the business relationships with its clients everywhere	Assist an enterprise to evaluate the benefit of the cooperation between enterprises	Assist an enterprise to search for potential enterprises to cooperate
Benefit	Enterprises can employ proper strategies to better utilize their resources	1. Strengthen the relationships between enterprises 2. Expand the service scope and range through cooperation between enterprises	Realize an information sharing platform between enterprises

object relationships and relationship measurements. The following subsections will detail these terms.

3.1.1 Objects

DSLML ontology defines four types of objects (Original Unit, Business Unit, Client Unit, and Business-Oriented Location Model) as shown in Figure 1 and defined in Table 2:

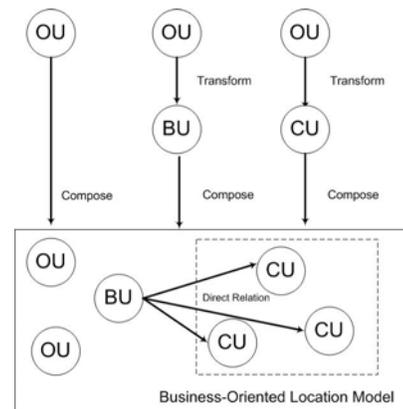


Figure 1. Objects in DSLML

Table 2 Objects definition in DSLM

<p>Definition :</p> <p>OU(Y) : Y is the Original Unit in the DSLM</p> <p>BU(C) : C is the Business Unit of the DSLM</p> <p>CU(D,C) : D is the client of Business Unit C in the DSLM</p> <p>$BOLM(C) = def \exists X_1, X_2, \dots, X_n$ is $CU(X_1, C), CU(X_2, C), \dots, CU(X_n, C)$</p> <p>$\exists Y_1, Y_2, \dots, Y_m$ is $OU(Y_1), OU(Y_2), \dots, OU(Y_m) \subset BOLM(C)$</p> <p>$\bigwedge_{i=1}^n \bigwedge_{j=1}^m (BU(C) \vee CU(X_i, C) \vee OU(Y_j))$</p>
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- Original Unit (OU): An entity in a map that is not at all referenced in the location model of an enterprise because of no business relationship between the enterprise and the entity. For instance, if there is no business relationship between a freight company A and a bookstore B, then B will be regarded as an OU in A's Business-Oriented Location Model.
- Business Unit (BU): Upon the construction of a Business-Oriented Location model for an enterprise, the OU representing the enterprise transforms into a BU.
- Client Unit (CU): An OU representing a client of the enterprise (constructing its Business-Oriented Location Model) transforms into a CU.
- Business-Oriented Location Model (BOLM): The BOLM of an enterprise is comprised of the BU (representing the enterprise), the CUs (denoting all of the clients of the enterprise, and OUs (symbolizing the entities without business relationships with the enterprise). For instance, if a logistic company C has three clients (D, E, F), then C's BOLM is composed of 1 BU representing C and 3 CUs denoting D, E, F, and a couple of OUs.

3.1.2 Object Relationship

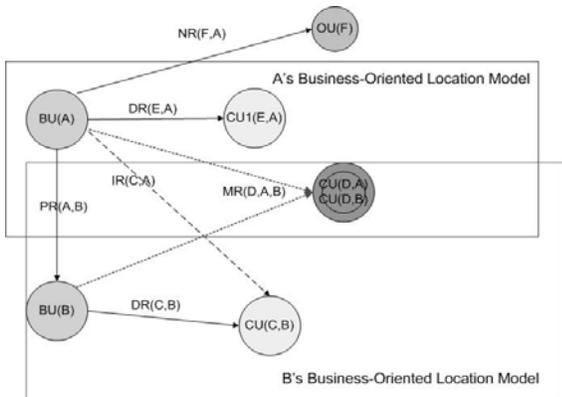


Figure 2 Object Relationships in DSLM

Table 3. Object Relationship definition in DSLM

<p>A is a Business Unit in BOLM(A)</p> <p>B is a Business Unit in BOLM(B)</p> <p>Definition :</p> <p>NL(F, A) : F is not located in BOLM(A)</p> <p>NR(F, A) : F has no relation with BU(A)</p> <p>LI (E, A) : E is located in BOLM(A)</p> <p>PR(A, B) : BU(A) and BU(B) has partner relation</p> <p>$DR(x, A) = \exists_x (LI(x, BOLM(A)) \wedge CU(x, A))$</p> <p>$IR (y, A) = \exists_y (NL(y, BOLM(A)) \wedge PR(A, B) \wedge CU(y, B))$</p>
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Object relationships stand for the relationships between the BU, CUs and the BOLM. There are a variety of relationships being modeled: Direct Relationship (DR), Indirect Relationship (IR), No Relationship (NR), Multiple Relationship (MR), Partner Relationship (PR), Located In (LI) and Not-Located In (NI) as shown in Figure 2 and defined in Table 3:

- Direct Relationship (DR): a relationship denoting the direct business relationship between a client and the enterprise such as DR(C, B) as shown in Figure 2 in which C is a client of the enterprise B.
- Partner Relationship (PR): a business relationship between two enterprises such as PR(A, B) as shown in Figure 2.
- Indirect Relationship (IR): a relationship between a client C (of the enterprise B) and the enterprise A that is formed because of a Partner Relationship between A and B such as IR(C, A) as shown in Figure 2.
- Multiple Relationship (MR): a relationship between a client and multiple enterprises that have the Partner Relationship such as MR(D, A, B) as shown in Figure 2 in which the client D is a client of both A and B (that further have the Partner Relationship with each other).
- No Relationship (NR): a relationship other than any of aforementioned relationships.
- Located In (LI): an inclusive relationship between a BU (CU, or OU) and a BOLM.
- Not-Located In (NI): a non-inclusive relationship between a BU (CU, or OU) and a BOLM.

3.1.3 Relationship Measurement

In order to differentiate the relationships for the purpose of decision support, relationship measurements are exerted to measure DR, IR, and MR. These measuring are based on the values of certain object attributes that an enterprise concerns such as average revenue and average order. Table 4, Table 5 and Table 6 exemplify certain algorithms for calculating the relationship measurements:

Table 4. Example of DR measurement

<p>Function Direct_Relation_Measurement (BU, CU)</p> <ol style="list-style-type: none"> 1. Select significant attributes A_i from BU that characterize the relationship between BU and CU, and transform their values to Semantic Levels SL_i according to BU's subjective judgment. 2. Assign weight W_i to all chosen attributes according to the levels of their significance to BU. 3. $DR = \sum_{i=1}^n SL_i * W_i$ <p>Note : This algorithm only exemplifies a linear measurement. Non-linear measurements can be employed in Step 3 as well.</p>
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Table 5. Example of IR measurement

<p>Function Indirect_Relation_Measurement (Source Enterprise BU, Target Enterprise BU, CU)</p> <ol style="list-style-type: none"> 1. Select significant attributes A_i from the client CU's Source Enterprise BU. Transform their values to Semantic Levels SL_i according to Target Enterprise BU's subjective judgment. 2. Assign weight W_i to all chosen attributes according to the levels of their significance to Target Enterprise BU. 3. $IR = \sum_{i=1}^n SL_i * W_i$ <p>Note : This algorithm only exemplifies a linear measurement. Non-linear measurements can be employed in Step 3 as well.</p>

Table 6. Example of MR measurement

<p>Function Multiple_Relation_Measurement (Source Enterprise BU, Target Enterprise BU, CU)</p> <ol style="list-style-type: none"> 1. Calculate DR(Source Enterprise BU, CU). 2. Source Enterprise BU calculates DR'(Target Enterprise BU, CU) by using the CU's attributes and data retained in Target Enterprise BU. 3. $MR = DR' - DR$

- DR measurement: Between the direct clients (CU) of an enterprise (BU), DR measurements aim to differentiate the clients. Table 4 exemplifies one possible way of such differentiation that is accomplished through the calculation of a weighted sum of the values of the chosen client's attributes.

- IR measurement: Between the indirect clients (CU) of an enterprise (Target Enterprise BU) because of its partnership with another enterprise (Source Enterprise BU), IR measurements intend to distinguish the indirect clients by calculating a weighted sum of the CU's attribute values gathered from Source Enterprise BU. However, the weights are assigned from the point view of Target Enterprise BU (instead of from Source Enterprise BU's).
- MR measurement: Given a MR (in which a client CU is associated with Source Enterprise BU and Target Enterprise BU by the MR bindings), MR measurements aims to further discriminate these bindings in terms of different originating perspectives (i.e., from the perspective of Source Enterprise BU). Table 6 shows the method for a MR measurement from the perspective of Source Enterprise BU. This MR measurement represents a strength difference between the DR measurement (of Source Enterprise BU and CU) and the DR' measurement (of Target Enterprise BU and CU) for which the retrieval of CU's data retained in Target Enterprise BU is made). In other words, from the perspective of Source Enterprise BU, a MR measurement reveals an important message about the subjective relative strength (with respect to Target Enterprise BU) in the regard of the relationship with the client CU. For instance, it manifests a stronger relationship Source Enterprise BU has with CU than that of Target Enterprise BU when the MR measurement is less than zero.

3.2 Mobile Enterprise Applications using DSLM

This section describes the three DSLM solutions (BOLM, PNLM, LPM) mentioned in Table 1. Each of the solutions supplies relevant decision-support aids and leads to certain integrations of enterprise business models and enterprise location models described in Section 3.1.

3.2.1 BOLM

A Business-Oriented Location Model (BOLM) (as defined in Table 2) represents a location model that is composed of the objects and the relationships that are embodied with semantics and are able to be dynamically expanded and updated as the myriad enterprise relationships develop with the clients. The construction of a BOLM for an enterprise involves the calculation of the DR measurements with respect to the enterprise clients and evolves these DR measurements with continuous interactions between the enterprise and the clients.

The application of a BOLM (e.g., deciding the service priorities for clients) accordingly involves consulting these relationship measurements together with additional myriad considerations (attributes) of service requests (e.g., request distance, request unit price, and request quantity for a logistic delivery service). For simplicity, a liner weighted scheme is exerted on the service attributes to attain the proportion of the significance share for a given service request (invoked by a given client) besides the other proportion of the significance share coming from relationship measurements. In section 4, we will exemplify the application of a BOLM and show its intended contributions.

3.2.2 PNLM

Partner-Network Location Model (PNLM) aims to enable information sharing and cooperation between cooperative enterprises. In addition, with PNLM an enterprise is able to evaluate the benefits of the cooperation.

Suppose a PNLM is formed because of the cooperation between enterprise A and B. The PNLM from A's perspective is then defined as in Table 7. A picturesque view of this PNLM is shown in Figure 3. (Figure 4 then shows that of the PNLM from B's perspective.) In other words, PNLM is constructed out of a PR relationship between A and B, and subsequent IR and MR generated. Since IR and MR are directional relationships, a PNLM accordingly is formulated as a directional model (i.e., from the perspective of A (or B)). The PNLMs from different perspectives differ from each other in terms of the different measurements calculated.

Table 7 Objects definition in PNLM

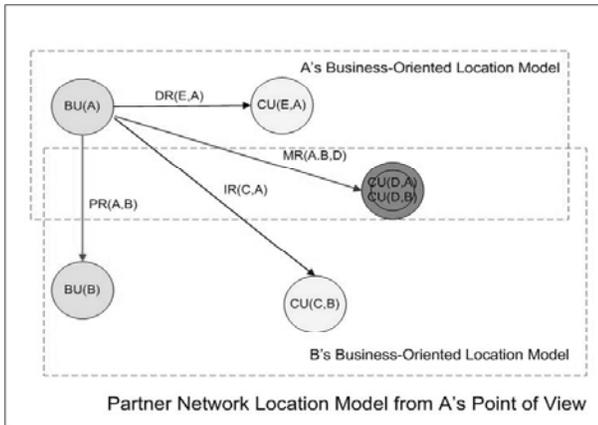
$$\begin{aligned}
 \text{PNLM}(A,AB) = \text{def } & \exists x_1, x_2, x_3, \dots, x_m \text{ is } \text{CU}(x_1, A), \\
 & \text{CU}(x_2, A) \\
 & \dots, \text{CU}(x_m, A) \\
 & \exists y_1, y_2, y_3, \dots, y_n \text{ is } \text{CU}(y_1, B), \text{CU}(y_2, B), \dots, \text{CU}(y_n, B) \\
 & \exists z_1, z_2, z_3, \dots, z_p \text{ is } \text{CU}(z_1, A), \text{CU}(z_2, A), \dots, \text{CU}(z_p, A) \\
 & \text{also is } \text{CU}(z_1, B), \text{CU}(z_2, B), \dots, \text{CU}(z_p, B) \\
 & \text{A and B have } \text{PR}(A, B) \\
 & \bigwedge_{i=1}^m \bigwedge_{j=1}^n \bigwedge_{k=1}^p (\text{BU}(A) \vee \text{BU}(B) \vee \text{CU}(x_i, A) \Big|_{\text{DR}(x_i, A)} \\
 & \vee \text{CU}(y_j, B) \Big|_{\text{IR}(y_j, B)} \vee \text{CU}(z_k, A) \Big|_{\text{MR}(z_k, A, B)})
 \end{aligned}$$


Figure 3. PNLM of enterprise A and B in A's point of view

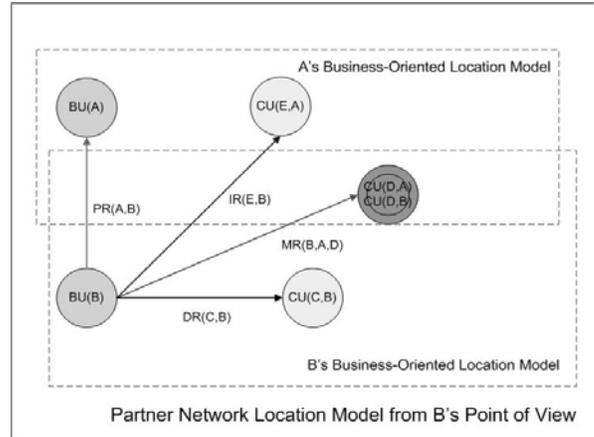


Figure 4. PNLM of enterprise A and B in B's point of view

The benefits of exerting PNLM in an enterprise are exemplified by two scenarios as shown below:

- Competitors cooperation scenario: Two competitive enterprises (such as the former Compaq and HP) cooperate through PNLM that facilitates things such as expanding market share in myriad regions, perceiving client relationships development, recognizing their services overlap, discerning the increase in their service scope, etc. This scenario emphasizes the importance of the number of clients increased because of the cooperation.
- Vertical supply chain scenario: A manufacture enterprise residing in southern Taiwan seeks a northern logistic enterprise to cooperate through PNLM for providing better services to the manufacture enterprise's clients in northern Taiwan. This scenario then emphasizes the increased relationship measurements because of the cooperation.

With the two aforementioned scenarios, a PNLM performance evaluation algorithm is provided (as shown in Table 8) for evaluating the performance of the cooperation with a Target Enterprise BU from the perspective of a Source Enterprise BU. The performance evaluation is represented as a vector comprising a CAN value and a SIM value. The CAN value denotes the increase in the number of the clients because of the cooperation between Source Enterprise BU and Target Enterprise BU, and the SIM value then stands for the increased relationship measurements because of the cooperation.

The rationale behind this performance vector is two-fold: (1) Different enterprise might have different objectives in the cooperation (as exemplified in the above scenarios) and thus the performance vector is unfolded as a vector of a CAN value and a SIM value (instead of a single scalar). (2) Rendering different [CAN, SIM] vectors (corresponding to different Target Enterprises) on a 2-dimension space, it is easy to snatch the various strengths between different enterprise cooperation.

Table 8. PNLM performance evaluation algorithm

<p>Function PNLM_Performance (PNLM, Source Enterprise BU, Target Enterprise BU)</p> <ol style="list-style-type: none"> 1. From the Source Enterprise's perspective, calculate the increase in CU because of the given PNLM and give rise to a statistics named a CAN value. 2. From the Source Enterprise's perspective, calculate the increased amount of measurements in relationships because of IR and MR encountered. This amount is named a SIM value. 3. Set the PNLM performance vector with respect to the Target Enterprise BU as a vector of [CAN, SIM]. <p>Note: If Source Enterprise BU cannot attain relevant client's attribute values (CU) from Target Enterprise BU during the calculation of the relationship measurements, then this CU would be considered as an OU. Source Enterprise BU subsequently calculates the relationship measurements in terms of the OU's attribute values.</p>
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3.2.3 LMP

Location Model Platform (LMP) is a platform for the exchange of BOLM abstracts. In other words, the shared BOLM abstracts empower the search of potential enterprises to cooperate without exposing enterprises' confidential and private information. Figure 5 shows an example of BOLM abstracts, and Table 9 lists the algorithm for producing BOLM abstracts.

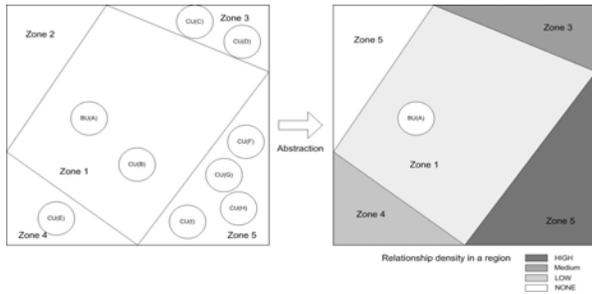


Figure 5. Example of BOLM Abstract

A BOLM abstract unfolds as a distribution of various business sizes on a designated geographical coverage that is composed of a certain number of geographical regions (as shown in Figure 5). The business size in a region is represented with a certain semantic label (High Density, Medium Density, or Low Density) that is allocated according to the relative strength of ongoing business occurring in the designated region with respect to that occurring in all of the regions. Ongoing business then is measured by the size of the clients and the size of the relationship measurements.

Table 9. BOLM abstract construction algorithm

<p>Function BOLM_Abstract_Construction (BOLM)</p> <ol style="list-style-type: none"> 1. From BOLM, identify all CUs that have direct relationship (DR) to the business. 2. In each geographical region, sum up all DR measurements and multiply this sum with the number of CUs in the region, obtaining a scalar representing a Region Relationship (RR). <ul style="list-style-type: none"> $\forall \text{ Region } R_j \subset \text{BOLM}(C), j=1, \dots, n;$ $CU(x_p, C) \subset R_j, p=1, \dots, m;$ $RR_j = \left(\sum_{p=1}^m DR(x_p, C) \right) * m$ 3. Total Region Relationship (TR) is the sum of all the RRs. <ul style="list-style-type: none"> $TR = \sum_{j=1}^n RR_j$ 4. Region Relationship Percentage is defined as the percentage of a designated RR to TR. <ul style="list-style-type: none"> $RRP_j = \frac{RR_j}{TR} \times 100\%, j = 1, \dots, n;$ 5. Assign Semantic Levels (region density) to RRs : <ul style="list-style-type: none"> • High Density : $100\% > RRP > \frac{100\%}{\text{total region}}$ • Medium Density : $\frac{100\%}{\text{total region}} > RRP > \frac{100\%}{m \times \text{total region}}$ • Low Density : $\frac{100\%}{m \times \text{total region}} > RRP > 0$ • None : $RRP=0$ <p>Note : m is a tuning parameter determined by the platform designer.</p> 6. Label the region density (the semantic level of RRP) in every region. 7. Return the labeled abstract.

4. Preliminary Evaluation

Our DSLM is implemented using the service-oriented architecture [10]. J2EE and Enterprise JavaBeans technology are used to develop the DSLM system (as shown in Figure 6). In this section, a logistic enterprise BOLM example is demonstrated on the task of service request arrangement.

In this logistic enterprise BOLM example, there are six types of clients (that are commonly perceived as shown in Table 10) that generate requests to the enterprise. Each request is composed of a variety of attribute values (such as request distance, request unit price, and request quantity). We assume there are limits set for request distance and request quantity in this example.

This example compares three different methods for the task of service request arrangement in terms of the average resulting value to the enterprise:

- First-In-First-Out: serving requests by the order of the request sequence.
- Far-Distance-Based: serving requests by the order of the request distances.
- BOLM: serving request by the order of client relationship measurements.

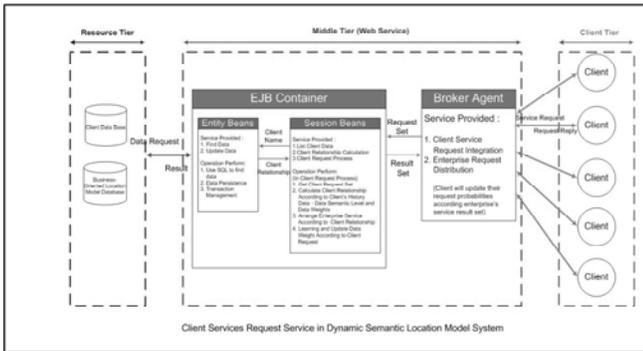


Figure 6. BOLM experiment system architecture

Table 10. Client request type in experiment environment

Client Type	Attribute	Request Distance	Request Quantity	Request Unit Price
1		Long	High	High
2		Short	High	High
3		Long	Low	High
4		Short	Low	High
5		Long	High	Low
6		Short	High	Low

*(Note: Request Distance: “Long” represents the range from 500 to 1300 and “short” from 100 to 499;

Request Quantity: “High” represents the range from 50 to 130 and “Low” from 10 to 49;

Request Revenue = Request Quantity * 1.5 (with High Request Unit Price);

Request Revenue = Request Quantity (with Low Request Unit Price);

Request Revenue is also multiplied by 3.5¹ while Request Distance is Long)

In Figure 6, Broker Agent pools 10 clients request (forming a request set) and sends them to the enterprise service arrangement method periodically. The request-sending magnitude of a client controls how often this client will post requests to the enterprise. Clients will tune their request-sending magnitude in the following ways: *if the enterprise rejects a client’s request, the client will tune down the request-sending magnitude, but will raise this magnitude vise versa*. The value of a request set (i.e., the 10 pooled client request per period) will be calculated with Equation 4-1 (in which the value of a request set for the logistic enterprise is proportional to the revenue received but reverse proportional to the distance transported and the quantity carried).

$$Request\ Set\ Value = Total\ Request\ Revenue / (Total\ Request\ Distance * Total\ Request\ Quantity) \quad (4-1)$$

A reply set is the arrangement results (with respect to a given request set) returned by the enterprise service arrangement method². Equation 4-2 computes the value of the reply set.

$$Reply\ Set\ Value = Total\ Reply\ Revenue / (Total\ Reply\ Distance * Total\ Reply\ Quantity) \quad (4-2)$$

Request Set Value and *Reply Set Value* are two metrics employed to evaluate the performance of the service arrangement methods. High *Request Set Value* indicates the continuity of intensive business opportunities, and high *Reply Set Value* then denotes quality arrangement between service requests.

Distinguished from *First-In-First-Out* and *Far-Distance-Base*, the BOLM method employs LMS weight update rule [2][8] to evolve the weights of the service-request attributes for the purpose of adaptively serving clients in light of the dynamic magnitudes of their requests. This adaptation aims at adjusting the weights toward the direction of high *Request Set Value* and high *Reply Set Value*. The weight learning equation is shown in Equation 4-3.

¹ The purpose of additionally tuning Request Revenue by 1.5 (3.5) is for making the comparison of the resulting values (for the six types of clients) more perceivable.

² Due to the limited resources of the enterprise, there might be client requests that cannot be served and hence are not taken into account in the client reply set.

$$Weight = Weight + learning\ rate * (Request\ set\ Value / Reply\ set\ Value) * Xi \quad (4-3)$$

*(Note: learning rate = 0.1; If the weight of the distance attribute is under tuning, then Xi represents the sum of distance in reply set.)

With the evaluation experiment setup addressed above, evaluation results show that the choice of the request arrangement method will affect the magnitudes of client requests, request set values, and reply set values. On the other hand, a good request arrangement method should be able to stably generate competitively high client request set values and enterprise reply set values by continuously well arranging the requests of the clients to serve.

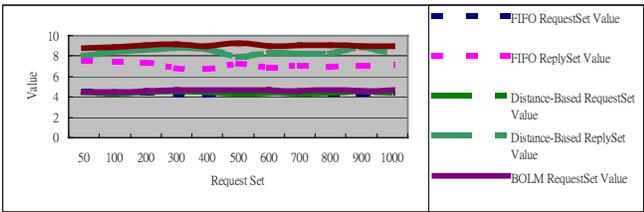


Figure 7. The evaluation results for the three request arrangement methods

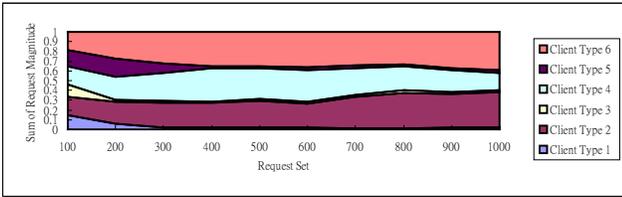


Figure 8. Client request magnitude changes in the FIFO method

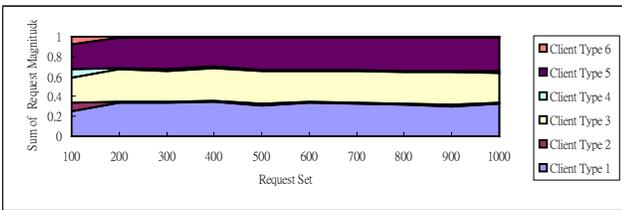


Figure 9. Client request magnitude changes in the Far-Distance-Based method

Table 11. Exemplars of a request set and the reply set obtained by the BOLM Method

Client Request Set are :
 The No.0 request set is :client = 2; distance = 404; revenue = 189; quantity = 126
 The No.1 request set is :client = 3; distance = 1156; revenue = 182; quantity = 52
 The No.2 request set is :client = 1; distance = 608; revenue = 309; quantity = 59
 The No.3 request set is :client = 6; distance = 143; revenue = 61; quantity = 41
 The No.4 request set is :client = 5; distance = 817; revenue = 73; quantity = 21
 The No.5 request set is :client = 1; distance = 1069; revenue = 346; quantity = 66
 The No.6 request set is :client = 6; distance = 139; revenue = 58; quantity = 39
 The No.7 request set is :client = 4; distance = 181; revenue = 66; quantity = 66
 The No.8 request set is :client = 2; distance = 319; revenue = 169; quantity = 113
 The No.9 request set is :client = 6; distance = 142; revenue = 42; quantity = 28
 request distance = 4978.0 request revenue = 1495.0
 request quantity = 611.0 request set value = 4.9152440952959

The Reply Set after Enterprise process are :
 The request set Enterprise accepted : client = 5; distance = 817; revenue = 73; quantity = 21
 The request set Enterprise accepted : client = 1; distance = 608; revenue = 309; quantity = 59
 The request set Enterprise accepted : client = 1; distance = 1069; revenue = 346; quantity = 66
 The request set Enterprise accepted : client = 2; distance = 404; revenue = 189; quantity = 126
 The request set Enterprise accepted : client = 2; distance = 319; revenue = 169; quantity = 113
 The request set Enterprise rejected : client = 3; distance = 1156; revenue = 182; quantity = 52
 The request set Enterprise accepted : client = 6; distance = 143; revenue = 61; quantity = 41
 The request set Enterprise accepted : client = 6; distance = 139; revenue = 58; quantity = 39
 The request set Enterprise accepted : client = 6; distance = 142; revenue = 42; quantity = 28
 The request set Enterprise rejected : client = 4; distance = 181; revenue = 66; quantity = 66
 reply distance = 3641.0 reply revenue = 1247.0
 reply quantity = 493.0 reply value = 6.947024896198523

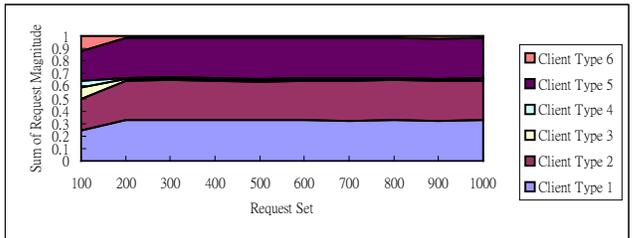


Figure 10. Client request magnitude changes in the BOLM method

We gradually experiment up to 1000 client request sets (an exemplar is shown in Table 11). That is, there are 10000 client requests in total sent to each request arrangement method. An investigation of which method can stably generate higher client request set values and enterprise reply values is explored. Figure 7 then shows the evaluation results in which the BOLM method outperforms the other two methods (FIFO and Far-Distance-Based) throughout the whole experiment process (i.e., from small number of request sets to great number of request sets). Furthermore, the two values stay quite stable throughout the experiment process with the BOLM method.

Figure 8, 9, 10 show the client request magnitude changes (i.e., the dynamics of the distribution of the requests) for the three request arrangement methods. In the FIFO method, the client types 2, 4, 6 that make Low distance requests are the higher request magnitude ones (i.e. with wider ranges along the dimension of Sum of Request Magnitude). In contrast, the client types 1, 3, 5 are the higher magnitude ones in the Far-Distance-Based method. However, in the BOLM method, the client types 1, 2, 5 are the higher magnitude ones. This is due to request revenue being computed by request distance and request quantity. The client types 1, 2 have High request quantity and the client type 5 has High distance compensation than the client type 6. In other words, the BOLM method is able to come up with valuable clients to serve.

5. Conclusion

The goal of Dynamic Semantic Location Model is to integrate enterprises business models with location models that have been playing a very important role in mobile commerce. Dynamic Semantic Location Modeling advances the former location modeling methods by embodying the dynamic and semantic features. Enterprises can build up their Business-Oriented Location Model first and then search for their potential partners in Location Model Platform. Finally, if the advanced cooperation between two enterprises can be possible, Partner Network Location Model will be constructed with their Business-Oriented Location Models. In conclusion, Dynamic Semantic Location Model provides certain solutions to enterprise-based LBS that take into account enterprise business models, transforming enterprises into high-end mobile enterprises. We have also evaluated Partner Network Location Model and Location Model Platform and created a few innovative scenarios about the integration of enterprise business models and the proposed location models. Our future work aims at realizing the proposed modeling method in a realistic domain, soliciting further adjustments required for practical exertion.

6. Reference

[1] Ericsson Enterprise (2002), "The path to the Mobile

Enterprise",

http://www.ericsson.com/products/whitepapers_pdf/whitepaper_mobile_enterprise_rc.pdf

- [2] Example for reinforcement learning: Playing Checkers (2001),
http://www.cs.wustl.edu/~sg/CS527_SP02/lecture2.html
- [3] Fetnet, http://enterprise.fetnet.net/event/Special_02.htm
- [4] H. Hiramatsu, (2001), "A Spatial Hypermedia Framework for Position-aware Information Delivery Systems", Lecture Notes in Computer Science, Vol. 2113, P. 754-763.
- [5] R. Jasper, M, Uschold (1999), "A Framework for Understanding and Classifying Ontology Applications", Twelfth Workshop on Knowledge Acquisition, Modeling and Management, Banff, Canada.
- [6] S. Domnitcheva (2001), "Location Modeling: State of the Art and Challenges", UbiComp Workshop on Location Modeling for Ubiquitous Computing, Atlanta, Georgia, USA.
- [7] S. Pradhan (2002), "Semantic Location", HP, <http://cooltown.hp.com/dev/wpapers/semantic/semantic.asp>
- [8] T. M. Mitchell (1997), "Machine Learning", pp.10 – 11, McGraw-Hill
- [9] U.vLeonhardt (1998), "Supporting Location-Awareness in Open Distributed Systems", PhD thesis, Department of Computing, Imperial College, London
- [10] V. Machiraju (2001), "Service-Oriented Research Opportunities in the in the World of Appliances", HP Software Technology Lab
- [11] Kai-Hsiang Peng and Soe-Tsyr Yuan (2002), "Location-Based Customized Voice Information Service for Mobile Community", *International Conference of Electronic Commerce*, HongKong, 2002.
- [12] Soe-Tsyr Yuan and Eva Tsao (2003), "A Recommendation Mechanism for Contextualized Mobile Advertising", *Expert Systems with Applications*, Vol. 24(4), pp. 399-414.