Simulating Shop-Around Behavior

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ABSTRACT

Shop-around spatial behaviors of downtown visitors are characterized as MultiPurpose-MultiStop (MPMS). However, the authors' investigations have revealed visitors frequently switch planned actions and generate improvised actions. By using an agent-based approach, especially with a medium-size specimen, simulating such spatial behaviors opens a rich vein of research, not only into such practical aspects as downtown revitalization but also several theoretical aspects. Based on data analysis, the authors have newly devised Agent Simulation of Shop-Around (ASSA). ASSA is a kind of activity-based model and each agent makes and remakes their schedule to visit shops based on time constraints and shop preferences, chooses alternative venues to visit when they fail in an errand, and makes impulse stops at shops and detour actions when time allows. A series of such activities carried out on one day will affect the next downtown visit schedule and so on. This paper refers to existing researches and briefly explains the features of ASSA, especially focusing on decomposition of the shop-around behaviors and the system components. The latest pilot ASSA ver.3 attempts a dynamic simulation of naturalistic and intelligent shopper behaviors. The authors then discuss the verifications by illustrating simulated performances in an actual shopping mall.

Keywords: *Agent-Based Modeling, Bounded Rationality, Dynamic Scheduling, Improvised Action, Learning and Adaptation, Planned Action, Shop-Around Behavior*

INTRODUCTION

The shop-around behavior model is also known as the MultiPurpose-MultiStop (MPMS) model and since the 1980s it has been developed and studied in such fields as geography and urban planning, not only for its practical application, e.g., downtown revitalization and town center management, but also for its theoretical interest in the field of spatial analysis (Kelly, 1981). By the 1990s, the application of the logit model that combines data-fitting and approximate utility-maximization, helped establish the 'Markov-chain type' models that make up transition probability OD-matrices. A typical microsimulation is Linked Logit and Poisson Model (LLPM), with a Poisson assumption on visitor arrival times. However, in the era of agent modeling, limitations pointed out concerning the Markov property, which ignores the personal history of downtown visitors, led to new approaches being explored.

The Logit model can be interpreted as used in an approximate estimation of the random utility, thus LLPM is considered to be a rational

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model. In other hands, the agent model would be considered as a bounded rational model, so there are at least two types of bounded rational models. One type is a rule-based approach that employs heuristics, which can be interpreted as an expression of 'procedural rationality,' as referred to by H. A. Simon. Implementation technologies such as the production system in knowledge engineering and advanced researches had already been made into this approach.

The other type is the assumption-relaxation approach, which relaxes the assumption of perfect rationality with perfect information by adopting the concepts of satisficing or the constraint satisfaction principle. This approach is also based on the 'satisficing principle' of mathematical models proposed by Simon and followers (e.g., Rubinstein, 1998).

In agent modeling research the daily activity-travel model has taken the lead in such fields as transportation planning (Table 1). Albatross (Arentze et al., 2001) is formulated as a rule-based system that guarantees data-fitting by employing a data-mining tool to generate heuristic rules (binary tree). Aurora (Arentze, Pelizaro, & Timmermans, 2005) is formulated as a utility-based theoretical model that generates a schedule by combining each activity (errand) that has non-linear S-shape utility and employing genetic algorithms; in addition, in response to an unexpected event such as congestion, the model carries out re-scheduling.

However, when the shop-around behavior model is compared to the daily activity-travel model that has the same MPMS structure, its characteristics can be found in human like planned actions and the improvised actions that down town visitors display; therefore, as a theme for research, the shop-around behavior model faces a higher degree of difficulty. There are few existing studies except Kurose, Bogers, and Timmermans (2001).

Our survey results show visitors frequently switch planned actions and engage in improvised actions. Based on data analysis, we have newly devised Agent Simulation of Shop-Around (ASSA) (Kaneda & Yoshida, 2008; Yoshida & Kaneda, 2012; Yoshida, 2010). ASSA is a kind of activity-based model and deals with agent spatial behaviors on shop-around trips in downtown areas. In ASSA, each agent makes and remakes their schedule to visit shops based on time constraints and shop preferences, chooses alternative venues to visit when they fail in an errand, and makes impulse stops at shops and detour actions when time allows. A chain of such activities on one day affects their plan for the next visit and so on. In this context, our agent is ”naturalistic and wise”; in short, their behavior is boundedly rational in the short term, but, by devising and implementing planning (dynamic scheduling/re-scheduling), and learning and adaptation functions, it is intellectual in the long term. In this paper, firstly we refer to existing researches and briefly explain the features of ASSA, especially focusing on decomposition of the shop-around behaviors and the system components. The current pilot version ASSA ver.3 attempts a dynamic simulation of naturalistic and intelligent shopper behaviors. Then, we discuss its verifications by illustrating the simulated performances in an actual shopping mall case.

AGENT SIMULATION OF SHOP AROUND (ASSA)–ITS CONCEPT AND STRUCTURE

Decomposition of Visitor's Shop-Around Behavior

The first feature of the downtown visitor's behavior modeled is the function of time allocation or scheduling of visits to shops under a limited time allowance (time budget). Implementing the scheduling function in itself was an antithesis of the Markov model, even if it does emphasize time constraint, and was an application of the intelligent planning function in the agent. Shop-around spatial behavior, as referred to here, has been explained in cognitive science (Hayes-Roths & Hayes-Roths, 1979).

The second feature modelled was dynamic updates as part of the agent's behavior, including mainly re-scheduling. This also relates to intellectual functions like adaptation and learning.

Table 1. Existing agent modeling researches

		Albatross	Aurora	Logit Model Approach (ex. LLPM: Linked Logit Poisson Model, Transition Matrix Models)	Kurose's Approach	ASSA ver.3
Deals with		Daily Activity-Travel	Daily Activity-Travel	Daily Activity-Travel / MultiPurpose-MultiStop in Shopping District	MultiPurpose-MultiStop in Shopping District	MultiPurpose-MultiStop in Shopping District
Principle of Modeling	Idea of The System	Heuristic-Rule Based	Attempts to Keep a Utility-Maximized Schedule under Constraints/ Events	Utility-Maximization Based	Heuristic-Rule Based	Utility/Constraints- Satisfaction Based
	Model Type	Bounded Rational	Bounded Rational but Adaptation/Intelligent Functions	Rational	Bounded Rational	Bounded Rational but Adaptation/Intelligent Functions
Adaptation / Intelligent Functions	Schedule Planning Function	YES but Conditional Rule Expression	YES	NO	YES but Conditional Rule Expression	YES
	Re-Scheduling	NO	Incremental-Type (Triggered by Congestion)	NO	NO	Recalculation-Type (Triggered by Errand- Failure, etc.)
	Preference Updating	NO	NO	NO	NO	Reinforcement Learning (to District State Change)
	Knowledge Extension of Mental Map	NO	Yes (Long-term Adaptation)	NO	NO	Not Yet, but Possible (Long-Term Adaptation)
Practicality	Data-Fitting Methods	by Machine-Learning (C4.5), Automatic Decision-Tree Forming	by GA, Non-Linear Utility Shape Estimation	by Classical Statistical Analysis, Utility and Probability Estimation	by Conditional classification	Some by Statistical Analysis, Some by Experiments, Other by Applying Hypothesis
	Case Study	Real Cases inc. a Benchmarking Case (of Hendrik-Ido-Ambacht and Zwijndrecht)	Numerical Illustration	Many Real Cases for Practical Uses	Real Case (of Veldhoven)	Real Case (of Ohsu, Kanayama, Nagoya)

Well data-fitness is the third feature of the agent behavior developed. The shop-around behavior to downtown Nagoya was investigated using over ten different survey results (Arakawa & Kaneda, 2002; Oiwa et al., 2005; Misaka et al., 2010). As part of the survey, visitors were asked about their walking routes, shops visited, and whether the visits to the shops were planned in advance. According to the redundancy analysis (Arakawa & Kaneda, 2002), the shop-around behavior within a survey area, including the routes taken and the distance traveled, were found not to be necessarily optimized. It was thus decided to decompose shop-around behavior into planned and improvised action. Improvised action was decomposed alternative-visit, and impulse actions (Table 2). Planned action was an action performed according to a schedule. Alternative-visit action is defined as an improvised action and involves visiting a shop that was not part of the original plan, because the planned errand was not completed in a shop visited. This concept was not specifically differentiated in Markov-type shop-around behavior models.

Basic Structure of ASSA

Our newly devised ASSA model consists of seven modules (Yoshida & Kaneda, 2008). Figure 1 shows the components of ASSA. There are three modules at the home-stage. One of them is the Downtown Visit Decision Module (VDM) in which various kinds of errands with the Poisson Arrival are pooled and concurrently with the arrival of the Time-Budget, an agent decides their visit to the downtown area. There are two types of trigger to a Downtown-Visit. One is the Time-Budget Arrival and the other is the State of the Errand Pool. The former can be said to be opportunistic and the latter demand-pull. Particularly, this model formulation can be interpreted as a similar kind to the classical Garbage Can Model (Cohen et al., 1972). This is also bounded-rational. Another module is the Schedule Planning Module (SPM), which has already been described. In the downtown area, this module is also called up at the time of Re-scheduling.

For agent spatial behavior downtown, four modules are important. First, the Route Choice Module (RCM) is called at the time of a planned visit to the next shop. The RCM uses the constraints of a mental map and preferences of each street, and deals with Detour-Action that selects one route under any constraints for the time allocated. If there is sufficient allocated time and a very appealing shop is found, an Impulse_Visit_Module (IVM) is called up.

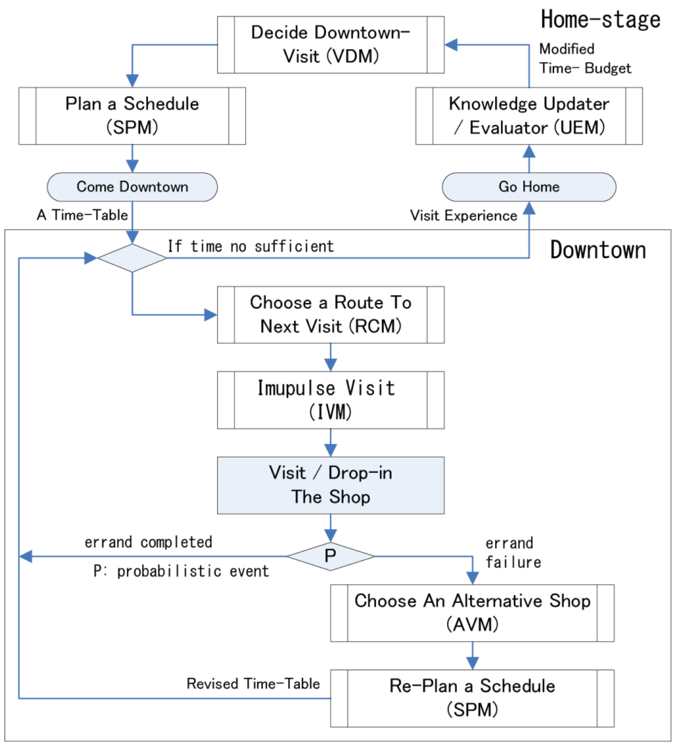
In the Planned Shop-Visit if an errand cannot be completed, an Alternative Visit Module (AVM) starts and from among a Recalled Shop Set, the module looks for a shop where the same type of errand can be fulfilled. If such a shop is found, Re-Scheduling starts. This procedure is repeated until no remaining errands or time is left.

At the home-stage, after visiting downtown, an Updater, Evaluator and Modifier (UEM) are

Table 2. Four-layered decomposition of shop-around behavior

Agent's Action		Information Processing		On Schedule Plan
		On Shop-Visit	On Path	
Planning & Decision Action		Planning a Visit-Order	Planning Path	Forming
Planned Action		Visiting Planned Shop in turn	Following Planned Path	Keeping
Improvised Action	Alternative-Visit Action	Choosing Same Category's Shop when Failed Errand	Modifying Path	Inserting
	Impulse Action	Impulse-Visit (Stop) Action: Dropping in Non-Planned Shop if Time Available	Impulse-Detour Action: Walking Non-Shortest Path if Time Available	Re-forming

Figure 1. Components of ASSA



called. As explained in the previous section, the items for updating are shop records, street preference and the mental map, and the updated items are the visited shop preferences and Customer Satisfaction (CS). The CS value can revise the Time-budget for the next visit so as to control the Downtown_Visit_Decision(VDM).

BOUNDED RATIONALITY IN HUMAN LIKE AGENT FORMALIZATION

The game theorist, Rubinstein (1998) classified bounded rationality based on the relaxation of some assumptions in rational decision problems as follows:

1. Lack of problem knowledge, and the constraints in a set of alternative plans in our case;
2. Ambiguity of preference. This is also the origin of bounded rationality; however, this can be revised through trial and error. This paper presents an example of shop-preference updating;
3. Computational competence, which is a theme researched in cognitive science, e.g., instant response; and
4. Lack of indifference to logical equivalent that concerns tie-break rules.

In addition, there can be an assumption that satisfies independence from irrelevant alternatives (IIA), H. A. Simon had already proposed the classical concept of the 'satisficing problem' in which a set of alternatives that satisfy an aspiration level or higher is considered to be a solution. Our model is designed, as much as possible, to explicitly deal with the above-mentioned bounded rationality. As other origins of bounded rationality, experimental studies have clarified inconsistencies such as the framing-effect and over-simplification (Tversky & Kahneman), and search for reason (Huber, Payne, & Puto).

For example, we show that the Schedule_Planning_Module (SPM) of ASSA is formalized as a satisficing problem (Example 1). This is a problem where visit-shops are selected from among a Recalled Shops Set, visits are ranked and the order is allocated in the Time-Table. There are three types of constraints: (1) the sum total of preference value for each visit-shop is at the value of the Aspiration Level or higher; (2) all activities including transfer do not conflict with each other and finish within the Time-Budget; and (3) the walking distance is also within the Aspiration Level.

Actually in our ASSA, the Schedule_Planning_Module (SPM) is to be formulated as a maximization problem forming a plan, a list of visit-shops in a Recalled Shop Set, using the goal function as the lexicographic order of the number of visit-shops, and the length of time, under the constraints of time and locations for errands given in advance. Furthermore, the plan is to be chosen from finite numbers of candidate plans; therefore this is an example that expresses bounded rational decision-making mainly based on a computational competence constraint (Example 2).

FEEDBACK FUNCTIONS OF A HUMANLIKE SHOP-AROUND AGENT

Customers dynamically change their behaviors in response to their downtown visit experiences. This section focuses on the four types of dynamic adaptation feedback that the ASSA model deals with, and explains them in the form of a short cycle.

Example 1. A formalization of the schedule planning module as a satisficing problem

Schedule_Planning_Problem(RS, TB):
Form $TT = [s^{(0)}, m^{(1)}, s^{(1)}, m^{(2)}, \cdots s^{(\mathrm{N})}, m^{(\mathrm{N}+1)}, s^{(\mathrm{N}+1)}]$
s.t.
(1) Evaluation Condition: $\Sigma_{j=1,\mathrm{N}}\ v^j \geq \mathrm{AL}_{EC}$
(2) Time Constraint: $\forall s^{(j)}, \forall m^{(j)}\ (j = 1 \cdots \mathrm{N})$,
$tb(TB) \leq tb(m^{(1)}) \wedge \forall j\ (= 1 \cdots \mathrm{N}),\ te(m^{(j)}) \leq tb(s^{(j)})$
$\wedge\ te(s^{(\mathrm{N})}) \leq tb(m^{(\mathrm{N}+1)}) \wedge te(m^{(\mathrm{N}+1)}) \leq te(TB)$
(3) Walk Length Constraint: $\Sigma_{n=1,\mathrm{N}+1}\ wl(m^{(n)}) \leq \mathrm{AL}_{ML}$

RS: A Set of Recalled Shops
TB: Given Time-Budget
TT: Time-Table
j: Shop id#, s^j : Visit Shop j,
$s^{(n)}$: n-th Visit Shop, *ordering function*: $j \mapsto n(j)$, one to one
$s^{(0)}$: Entry Point, $s^{(\mathrm{N}+1)}$: Exit Point
$m^{(j)}$: Move to j-th Shop
v^j : Evaluation Value to s^j
$tb(\bullet)$: Begin-Time, $te(\bullet)$: End-Time,
$t\hat{d}(\bullet)$: Estimated Duration Time, $te(\bullet) = tb(\bullet) + t\hat{d}(\bullet)$
$wl(m)$: Walk Length of Move m
AL_*: Aspiration Level of Constraint $*$

Example 2. Formulation of schedule planning module

```
Procedure SchedulePlanning (SPM)
begin
 MaxPlan := 10;
 For CandidatePlan := 1 to MaxPlan do
  Assign each shop to each errand
   from the set of recalled shop (RS)
    (by the evaluation value);
  Make the set of planned visits (VS)
  Make the order of the shops
   (by the evaluation values);
  MaxOrder := #(VS) ;
  for rank := 1 to MaxOrder do
   while enough time do
    if the errand is fixed then
     if no conflict to other errands then
      Insert the shop-visit on
       Time-Table within Time-Budget ;
     end
    elseif no conflict to other errands then
     Insert the shop-visit on Time-Table
      within Time-Budget on Time-Table;
    end
   end
  end
  Cancel remain errands
   (bring them back to the errand pool);
  Decide Time-Table;
 end
 Choose one Time-Table
  by Maximization to Lexicographic-Order of
   (1) #(VS),
   (2) tb(s[0]) - te(s[N+1]) (time-length);
end.
```

1. Re-Schedule Planning

An agent not only creates a schedule plan before a downtown visit, but also carries out re-scheduling when the current plan is not fulfilled due to a time delay, caused by such factors as alternative shop visits or impulse visits. Re-scheduling may be carried out several times within the downtown visit.

2. Updating on Shop-Preferences

An errand completion is given stochastically. Each shop preference depends on a relationship between the customer and a shop; therefore, preference values are updated. This update is made once for each shop visit. If the configuration of shops within the downtown area does not change, the agent empirically acquires stable behavior over ten downtown visits; however if the shop configuration is dynamic, the behavior of the agent is to follow them with a time delay.

3. Extension of the Mental Map through Walking Exploration

As a result of the exploration of streets or shops, for each downtown-visit, the agent has an expanding mental map; however, depending on the frequency of visits, due to forgetfulness the agent may partially fail to remember information on the map, thus requiring a Recalled Shops Set to be changed.

4. Modification of the Next Downtown-Visit through Customer Satisfaction (CS) Evaluations

The final evaluation of each downtown-visit is made in accordance with customer satisfaction (CS). The CS will be a composition of variables such as safety, enjoyment and surprise, as well as errand completion efficiency. CS evaluation is conducted once per downtown visit. According to the evaluation value, the frequency and length of the Time-Budget for the next visit can be affected.

In ASSA, the shop-preference values are revised based only on the visit result of each shop. Evaluation information (reward) is only considered to be instruction information without a teacher; therefore the mechanism can be interpreted as a kind of reinforcement learning.

ASSA ver.3 – CURRENT PILOT VERSION

Version-Up History of ASSA – From ver.1 to ver.3

ASSA ver.1 deals only with Planned Action and Alternative Action (task completion / failure is represented as a fixed probability for each errand). The re-scheduling module (SPM) is called up in the case of a failure to complete an errand. Moreover, the tight assumption presupposes that all of the 'path planning' is always optimized by the Dijkstra method.

In ASSA ver.2, we implement Impulse Visit Action. The impulse for each Impulse Visit Action is determined probabilistically, assuming there is enough remaining time, and is based on the so-called street appeal, the sum of the shop preferences along the street, and uses the e-greedy method (for more details, see Yoshida & Kaneda, 2008b).

ASSA ver.3 adds two kinds of Detour Action: one concerns the relaxation of the optimality of path planning, and the other the taking of a detour on impulse. The former deals with 'subjective length' as a weight set at each street. These weights are also updated though experience by using a similar algorithm as shop-preference updating. In Impulse-Detour Action, several studies had appeared such as Dijkstra, Timmermans, and Vries (2007), but no study deals with the time-constraint. We newly devised an algorithm similar to the one used by Impulse Visit's, and this time, the softmax method with Boltzmann distribution was used to model this behavior.

Implementation of ASSA ver.3

In this section, we refer to ASSA ver.3, the latest pilot implementation version which implements a partial framework of ASSA (for details, see Yoshida, 2010).

ASSA ver.3 is set using the following major assumptions:

1. The hinterland structure is mono-centric, in other words, there is only one prominent commercial center in the whole area;
2. Interaction between visitor agents is omitted in the district;
3. All agents already know all shops and routes, in other words, the agents have a complete mental map.

At the home-stage VDM is a Garbage Can Model in which the visit decision possibility is an increasing function of an accumulation of seven types of errands (Poisson accumulation; for details, see Yoshida & Kaneda, 2007). It means a demand-pull decision. As before SPM had already been explained. Based on the survey results, the standard length of the Time-Budget is given to each of four types of agent attributes such as gender, age, the distance from home, and transport-means. All shops in the district are assumed to be already known, i.e., recalled shops. There is also an assumption that the same probability of completing an errand is given for each shop type.

In downtown, the RCM is implemented as the shortest path seeker under each modified length by 'subjective' weight as mentioned before. In the AVM, when the agent has failed, they choose an alternative shop according to probability using the e-greedy method for a preference value that is based on the remaining time-distance ratio.

After a downtown-visit, only the shop-preference values are updated in the UEM. The CS value does not affect the next downtown visit decisions.

SIMULATION PERFORMANCE OF ASSA ver.3

Evaluation Framework of ASSA

In this paper, from the standpoint of such 'constructive modeling,' we adopted a traditional dichotomy found in urban simulation fields; system verification and model validation.

System verification is used as the completeness of coding intuitively, or 'No Bug proof.' Agent simulators have also become complicated as computer software, so in such cases, a software development framework should be applied.

Model validation consists of at least two parts; (1) the soundness of model 'structural' formulation in comparison with the nature of a problem entity, and (2) the goodness of data-fittings of major parameters in the designed model. Model validation affects mainly forecastability or explainability of the simulation results. Although the former model structures are created through insightful observation, calibration processing is mainly required at the latter phase.

To evaluate the characteristics of the above designed model, ASSA ver.3 has been analyzed taking into account the following five aspects.

a. General Evaluation

1. Analysis of statistics (for basic model validation);
2. Analysis of aggregated behavior (for basic model validation).

b. Individual Function Evaluation

1. Illustration of agent's individual behavior (for system verification as an intelligent agent);
2. Analysis of similarity of visit sequence (for model validation as an intelligent agent);
3. Analysis of redundancy (for model validation as an intelligent agent).

In this paper, we focus on points 1, 2, and 3 (see Yoshida & Kaneda, 2012; Yoshida, 2010, in the detail results of the others). From the data obtained in the simulation, individual behavior results were extracted for each agent, and then graphically represented on a map. There are two focal points: shops visited and walking routes. For shops visited, attention is paid to the following four variables: locations, visiting order, planned or unplanned visits, errand completion or failure. Based on our observations, each of the following designed functions was verified as working: validity of a plan drawn up by an agent in the downtown visit decision; implementation of the plan in the planned actions; occurrence of alternative visits; and occurrence of impulsive visits. Walking routes were assessed mainly by whether agents deviated from the shortest route by checking the initial planning and implementation of a planned route, and the occurrence of detours from the planned route.

This paper deals with Asunal Kanayama, Nagoya, a three-storied shopping mall with 60 shops divided into 28 commodity stores, 15 cafes and restaurants, 15 services and 2 wagons, and 3 neighbors. Detailed survey data had already been obtained (Misaka et al., 2010). Visitors were categorized by gender, three age groups and other attributes such as the location of domicile and visit frequency. In this shopping mall case, the performances of 3,000 agents during 120 holidays were recorded and found to be stable after a trial 30 holidays.

Simulation Performance of ASSA ver.3

Table 3 shows comparisons between survey data and the simulation results obtained using ASSA ver.1, 2, and 3. Please note that the simulators used time distance expression, whereas the actual physical distance traveled was extracted from the route drawn on the maps of the surveys, making comparison between the two impossible. Therefore, the distance traveled is shown only for reference. Free walking speed is generally said to be between 1.2 m/s and 1.5 m/s. If the simulation data is converted into distance using these values, the distances traveled fall in the range of 172 to 216 m, 65 to 81 m, and 238 to 297 m for ASSAver.1, 2 and 3, respectively. Comparing other values, it is evident that the duration of a visit to the commercial district is shorter by approximately 14 minutes, and the numbers of facilities visited is about 0.7 facilities fewer for ASSA ver.3 compared with the survey data. The simulations showed realistic values for planned facility visits.

Figures 2 (a) and 2 (b) show the results of aggregated behavior analysis with a focus on pedestrian passage percentage distribution. With regard to the ground floor of the Kanayama mall, it is apparent that the simulation results almost match the survey data. On the 2nd and 3rd floors, the simulation shows fewer visits than the survey. To remedy this fact, the following adjustments can be made: weaken the negative effect of distance when shops are selected; and to improve parameters for the preference of shops and streets; adjust the negative effect of visiting higher levels in multistory shops.

Here, we will explain the typical performance of four agents, each of which illustrates the elemental functions we had devised.

Test 1 – Verification of Planned Action

Figure 3 shows the walking route of Agent A: a middle-aged male living near the downtown area and arriving by train. He had planned to enter a station entrance on the 2F, to visit a general store (1) and clothing store (2), and to return to a station exit on the 1F. Actually, he did enter from the 2F, went up to the 3F, visited store (1) and completed his first errand, then visited store (2) and also complete his second errand. Then, he went down to 1F and exited the mall, all as planned. Basically, his walking route is the shortest path, so this case shows that this scheduling function works well.

Test 2 – Verification of Alternative Visit and Re-Scheduling

Figure 4 shows the walking route of Agent B: a young female also living near the downtown area and arriving by train. Her original plan was to enter from a subway entrance on the 1F, to go to neighbor (1), to go up to a general store (2) on the 3F, to go down and to go to neighbor (3), to go to neighbor (5), and return to an exit on the 1F. We can observe that this route is the shortest path under some time-constraints such

Table 3. Aggregated results for ASSA ver.1, 2 & 3 in the Kanayama Mall Case

	ASSAver.1	ASSAver.2	ASSAver.3	Survey
Avg. Stay Time (min.)	54	70	80	94
Avg. Walk Time (m) /time (min.)	2.4min	0.9min	3.3min	147m
Avg. # of Visited Shops	1.07	1.85	2.11	2.84
Avg. # of Planned-Visit Shops	0.74	0.71	0.61	0.63

Figure 2. Pedestrian spatial distributions in the Kanayama Mall Case

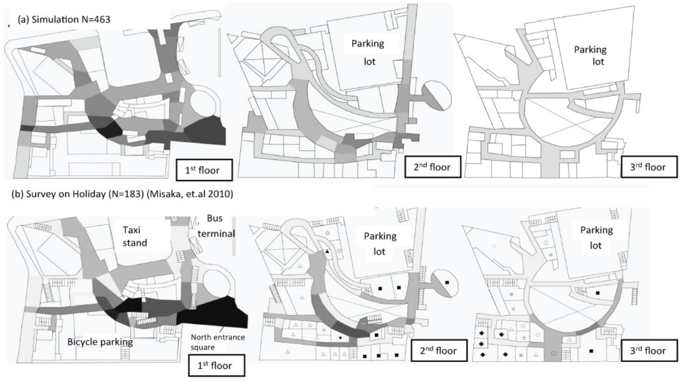
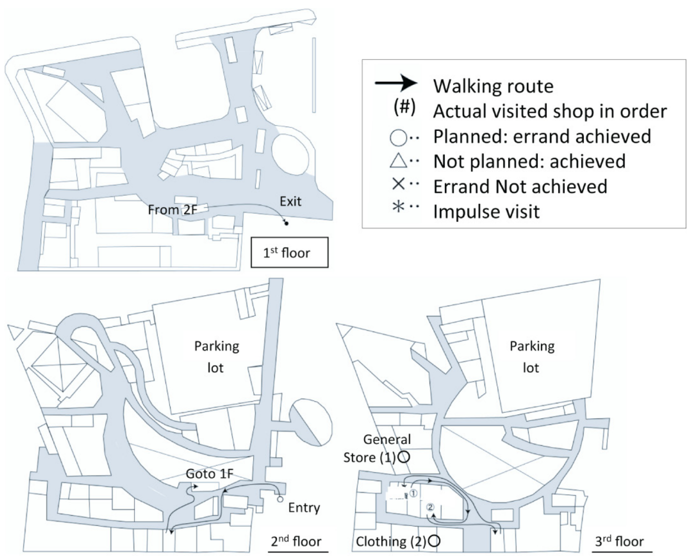


Figure 3. Planning action in Agent-A's performance



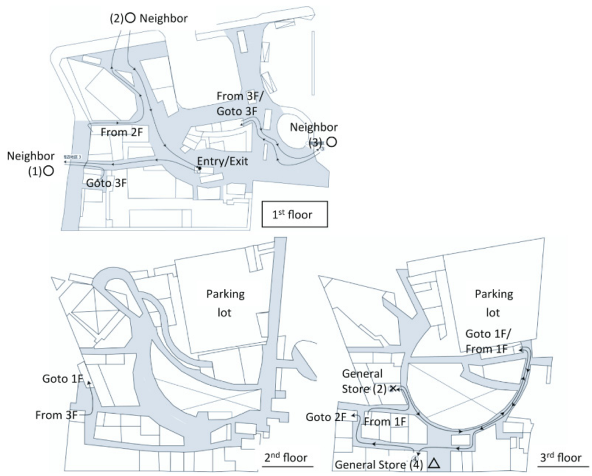
as (3) that is set at the start time. However, as she couldn't achieve her errand at (2), she needed to visit general store (4). But a promise time was close to go to (3), in advance she went down to neighbor (3) on the 1F and after completing this errand, she went back to 3F and visited (4). After completing her errand at (4), she went down and on to visit neighbor (2), and at last returned.

In this case we can verify that agents have both an alternative action function and a re-scheduling function.

Test 3 – Verification of Impulse Visits

Figure 5 shows the walking route of Agent C: also a young female, living near the downtown area and arriving by train. Her original plan was only to visit neighbor (3). But when observing her route we find that on the way to her destination she first visited a restaurant (1) followed by a Music CD store (2), clearly demonstrating typical impulse visits. In other words, we can say that the visits were the results of improvisation in the model. From this, we verify the proper

Figure 4. Alternative visit and re-scheduling in Agent B's performance



performance of impulse visit behavior, which is implemented in ASSA.

Test 4 – Verification of Detour Action

Figure 6 shows the walking route of Agent D: a senior male living near the downtown area and arriving by car. His original plan was to start from the parking lot on the 2F, to go down to the 1F and on to neighbor (1), and then to neighbor (3), and finally return to the parking lot. But in this case, his performance included impulse visits to a music CD store (2), other (4) and a restaurant (5).

Here, pay attention to his walking route after his completed visit (3), in this case, the shortest return route from (3) is to simply walk back along the north side lane, but he didn't like to re-trace his steps. He walked toward the east, enjoying the detour and making impulse visits, so his performance in ASSA is a combi-

Figure 5. Impulse visits in Agent C's performance

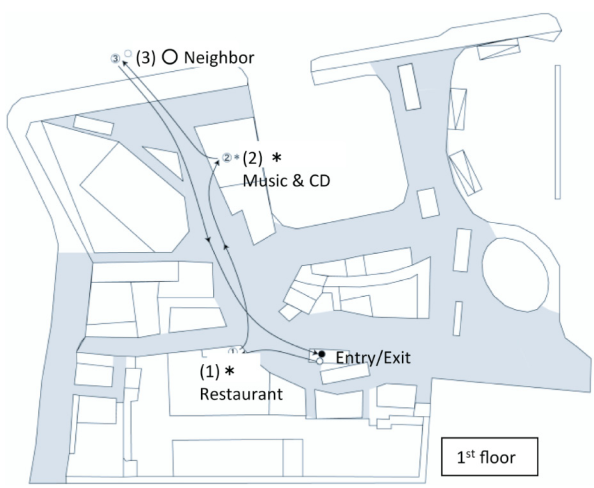
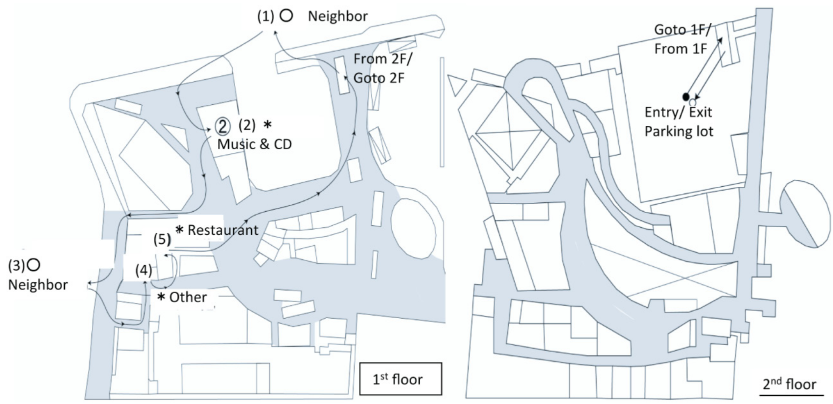


Figure 6. Detour action in Agent D's performance



nation of improvised actions typical of down town visitors.

CONCLUSION

ASSA deals with downtown visitor shop-around spatial behaviors. From the constructive approach viewpoint of a 'human-like' agent, an integration of bounded rationality and feedback modifications of the agent's behaviors were explained as the key idea of ASSA study. For verifying and validating the current pilot version ASSA ver.3, based on an actual survey, some typical simulation performances including several agent spatial behaviors were illustrated in the three-storied Kanayama shopping mall case.

Dynamic scheduling is one of the key features of ASSA, as well as the improvisation of downtown visitor actions within the time-budget, as opposed to the existing Markov-type models. The simulated performances such as planned actions, improvised actions (alternative visits, impulse visits and detour actions) are examined.

About further research, we would like to refer to two topics. One is the relaxation of the 'completeness of a mental map,' so in such cases, a utility function inside a shop-around agent is required, though we have already devised a theoretical consideration by introducing decision sciences (Kaneda & Yoshida, 2008). Another is about the parameter tuning problem. In our ASSA study, several of the parameters were tuned in an ad-hoc way. Artificial Intelligence aided statistical estimation methods are expected.

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