Semantic Ideation Learning for Agent-Based E-Brainstorming

Soe-Tsyr Yuan and Yen-Chuan Chen

Abstract—Brainstorming can assist organizations in generating creative ideas using teamwork and collaboration. However, the role of information technology in brainstorming is merely that of an assistant that passively supports the progression of brainstorming sessions rather than proactively engaging in the sessions. This paper integrates the unique association thinking of humans with an intelligent agent technique to devise an automated decision agent called the Semantic Ideation Learning Agent (SILA) that can represent a session participant who is actively participating in brainstorming. SILAs are grounded on the three association capabilities of human thinking (similarity, contiguity, and contrast). Furthermore, a Collective Brainstorming Decision System (CBDS) is built to construct an environment where SILAs can learn and share their knowledge with each other. Additionally, CBDS is integrated into an intelligent care project (iCare) for the purpose of innovated e-service recommendation. Preliminarily, evaluation results indicate that the proposed system advances e-brainstorming by crossing the three key boundaries of human ideation capability (understanding, cognition boundary, and endurance).

Index Terms—E-brainstorming, intelligent agents, ontology, Q-learning.

1 Introduction

Brainstorming is an effective means of "getting a large number of ideas from a small number of people in a short time" [1]. Brainstorming can help organizations and individuals in generating creative ideas through teamwork and collaboration. Creativity then refers to the ability of bringing something new into being for some purpose. In this paper, we shared a definition of creativity developed by the organizational psychologist Reginald Talbot [2], who defined creativity as "making a change that sticks." The word "making" indicates that creativity is about bringing something into being. The word "change" means the introduction of something new, which can fall anywhere along the continuum from continuous change (that is, incremental improvement) to discontinuous change (that is, paradigm breaking). The phrase "that sticks" then indicates that the creative product or idea serves some need or purpose.

E-brainstorming is a form of brainstorming that employs computer-mediated electronic communication to replace verbal communications [3]. E-brainstorming often utilizes special software that gathers employees' ideas and shares them with other group members to encourage faster collaboration. In general, e-brainstorming generates more ideas than verbal brainstorming groups [4]. This improvement of e-brainstorming over the conventional brainstorming process comes from factors such as production blocking and evaluation apprehension [5].

Furthermore, the number of ideas generated has been viewed as the dominant measure of e-brainstorming effectiveness [6], [7], [8]. (The issue of opportunities to build relationships with other people or individual growth is beyond the scope of this study.) This work seeks to consider whether the effectiveness of e-brainstorming could further be enhanced. Furthermore, aside from improving group creativity, this study explores the application of idea generation to the era of the service economy. This study seeks to better understand human's capabilities in generating ideas and attempts to devise an architecture and inference mechanism adopted by intelligent agents in order to achieve effective e-brainstorming (which might be useful to some intelligent e-services).

This study develops an inference mechanism of Semantic Ideation Learning Agent (SILA), which performs idea associations and generation, and an architecture of Collective Brainstorming Decision System (CBDS), which provides an environment where SILAs could learn and share their knowledge. These intelligent agents could not only represent the session participants and attend brainstorming session when they could not be present but also report the session process and productions to their clients after completing the brainstorming discussion. Moreover, this agent-based e-brainstorming was applied to an Intelligent Care Service (iCare) Project [9] and used to recommend innovative services to the elderly at home. Additionally, simulations and preliminary evaluations were undertaken in order to justify the values of SILA and CBDS to e-brainstorming within the context of the iCare Project domain.

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2 Brainstorming Review

Brainstorming is one of the best known tools for creative problem solving. The term *brainstorming* was first used by Osborn [10]. Brainstorming can simply be defined as a group process for generating ideas by using the four divergent thinking guidelines, namely, deferring judgment (the process of stopping to judge ideas and options until after there are many ideas generated), striving for quantity (more ideas generated leads to higher quality ideas), freewheeling (giving participants the opportunity to be playful and to strive for imagination), and seeking combinations (creating ideas that are based upon previously stated ideas). Accordingly, brainstorming engenders synergy; that is, an idea from one participant can trigger a new idea in another participant, who would otherwise not have been produced the idea.

E-brainstorming utilizes electronic communication to replace verbal communications and thus eliminates problems such as production blocking. For example, group support systems (GSSs) have been applied to assist in the idea generation process. A GSS is a suite of collaborative software tools that operates over a computer network and allows people to anonymously contribute ideas. Some works have revealed that the application of GSS in idea generation improves both the quantity and the quality of ideas generated [11], [12], [13], [14], [15]. Satzinger et al. [16] further indicated that the types of ideas generated are affected by the stimulus contained within a GSS group memory.

Most ideation research either implicitly or explicitly assumes Osborn's conjecture that if people generate more ideas, then they will produce more good ideas. Osborn [17] reported evidence that people generate more good ideas in the second half of a brainstorming session than during the first half. Some studies have also reported that certain ideation protocols can elevate both idea quantity and idea quality [18]. However, another work reported no relationship between idea quality and idea quantity [19]. That is, previous ideation literatures were inconsistent in the arguments.

Briggs and Reinig [20] provided a theoretical explanation (Bounded Ideation Theory) to clarify the relationship between idea quantity and idea quality, and they recommended guidance for the development of ideation techniques for improving the quality of ideas. A good idea was defined as one that is feasible to implement and would attain the goal. The Bounded Ideation Theory was a causal model of the ideation function (the relationship between the cumulative number of good ideas contributed during an ideation process and the total number of ideas generated).

Their causal model identified three essential boundaries of the human ideation capability (an understanding boundary, a cognitive boundary, and an endurance boundary) that influence the production of good ideas. The understanding boundary indicates that the relationship between the number of good ideas and the total number of ideas becomes a curvilinear function with a positive but decreasing slope once an understanding of the task has been achieved. The cognitive boundary signifies that because of the lack of additional external stimuli to activate a new part of the group memory, people tend to think inside the box, causing subsequent contributions to increasingly become similar to previous contributions, thus yielding fewer new good ideas (that is, the declining ratio of good ideas to the total ideas over time produces an ideation function with a positive but decreasing slope). The endurance boundary signifies that because an individual's mental and physical abilities diminish with effort over time, ideation abilities will then decline as ideation proceeds (that is, if the ideation process were to continue for a sufficiently long duration, then participants might lose the ability to generate good ideas, which leads to a falling ratio of good ideas to the total ideas over time and yields an ideation function with a positive but decreasing slope).

Considering the aforementioned review of the past brainstorming literature, this study argues that idea quantity could be considered as the dominant measure of e-brainstorming effectiveness when adopting an ideation protocol that resolves the problems associated with the three boundaries (understanding boundary, cognitive boundary, and endurance boundary). That is, the current state of the art of e-brainstorming could possibly be advanced in the following directions:

1. *Learning capability for understanding the task.* As ideation proceeds, ideation participants need to share and learn more information for a better understanding of the task and to be able to generate ideas. Moreover, the causality among the generated ideas should be easy to characterize and then record in the group memory.
2. *Continued adoption of additional external stimuli.* As ideation proceeds, ideation participants should move beyond the limits of their working memory and simultaneously think about all concepts on their knowledge network.
3. *Alleviation of attention exhaustion.* In the conventional brainstorming process, participants are simultaneously present in the same place, think of ideas, and voice their opinions to the group members. Although current e-brainstorming overcomes the spatial and distance limitation of conventional brainstorming with the technique of electronic communication, all participants must still be present at the brainstorming session at the same time to proceed with the discussion.

These possible advancement directions subsequently serve as the guidelines of the development of our agent-based ideation architecture and inference mechanism (which is described in detail in Section 4).

3 The Basic Concepts

To make an intelligent agent capable of generating ideas, the preliminary work investigates three fundamental human's association capabilities (similarity, contiguity, and contrast) during idea generation [10], implements these capabilities in an agent's inference mechanism, and unfolds the design of SILA, which performs idea associations (based on a devised ontology-based representation of ideas). A SILA represents an ideation participant that can learn to understand the task and adopt external stimuli, free from limits in working memory and from attention exhaustion. CBDS is the ideation architecture and environment with which SILAs could learn and share their knowledge with each other. This study shows the preliminary results of this agent-based ideation architecture and inference mechanism.

Osborn noted that almost all idea generation activities rely on the association of ideas. Association encourages

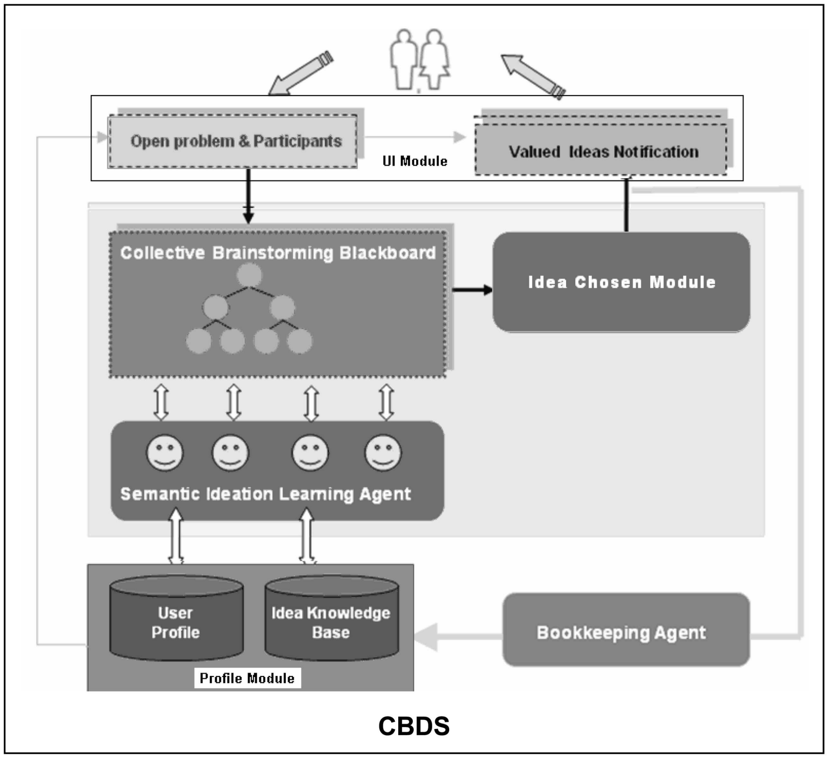


Fig. 1. CBDS—System architecture and environment.

imagination and causes one thought to lead to another. The ancient Greeks laid down the three patterns of associations:

1. *Association by contiguity.* This indicates "proximity," like a baby's shoe reminding someone of an infant.
2. *Association by similarity.* An example of this is a picture of a lion might remind someone of their cat.
3. *Association by contrast.* An example of this is a midget who might remind the viewer of a giant.

The three association patterns are accordingly introduced to the inference mechanism of SILA ideation agents in order to allow autonomous idea generation. This SILA design can further enhance the number of ideas generated (that is, the dominant measure of e-brainstorming effectiveness) by removing the limitations, as mentioned in the Bounded Ideation Theory. We argue that this concept of autonomous idea generation can create a new perspective of recommender systems (which might be valuable to the service economy in terms of innovative service discovery and recommendation).

4 System Architecture and Environment

This system aims at constructing a new e-brainstorming decision model, integrating semantic expression with the three ideation association capabilities into SILA agents that are supported and facilitated with the system architecture of CBDS. As depicted in Fig. 1, the architecture and the environment have several components. Fig. 2 provides an overall high-level description of the interactions between the main components of the system.

These parts and their interactions are described as follows:

1. UI Module. This module has two components:

   - Open Problem and Participants Component. An "open problem" is an initial topic or issue given to the system. This study defines an open problem as an idea instance represented by a specification defined in our idea ontology. "Participants" means the clients attending the brainstorming session, where every client is associated with an intelligent agent (SILA) that serves as the client's representative to deal with idea association. The Open Problem and Participants Component represents the given open problem and the participants and sends two input parameters, *Initial Idea* and *Clients*, to CBDS. That is, this study assumes the existence of an initial idea instance (possibly obtained from a user's needs) and a given set of ideation participants.
   - Valued Ideas Notification Component. This receives the set of valued ideas and the ideation map from the Idea Chosen Module and delivers them to the session participants. Hence, the participants cannot only obtain successful results from brainstorming but also discover the causality among ideas.

2. Profile Module. This comprises two parts: User Profile and Idea Knowledge Base. The User Profile stores fundamental information about a client. The Idea Knowledge Base records every client's domain knowledge, which comprises idea instances and the relationships between these instances. That is, this study assumes the existence of a given set of ideation participants and their relevant knowledge.

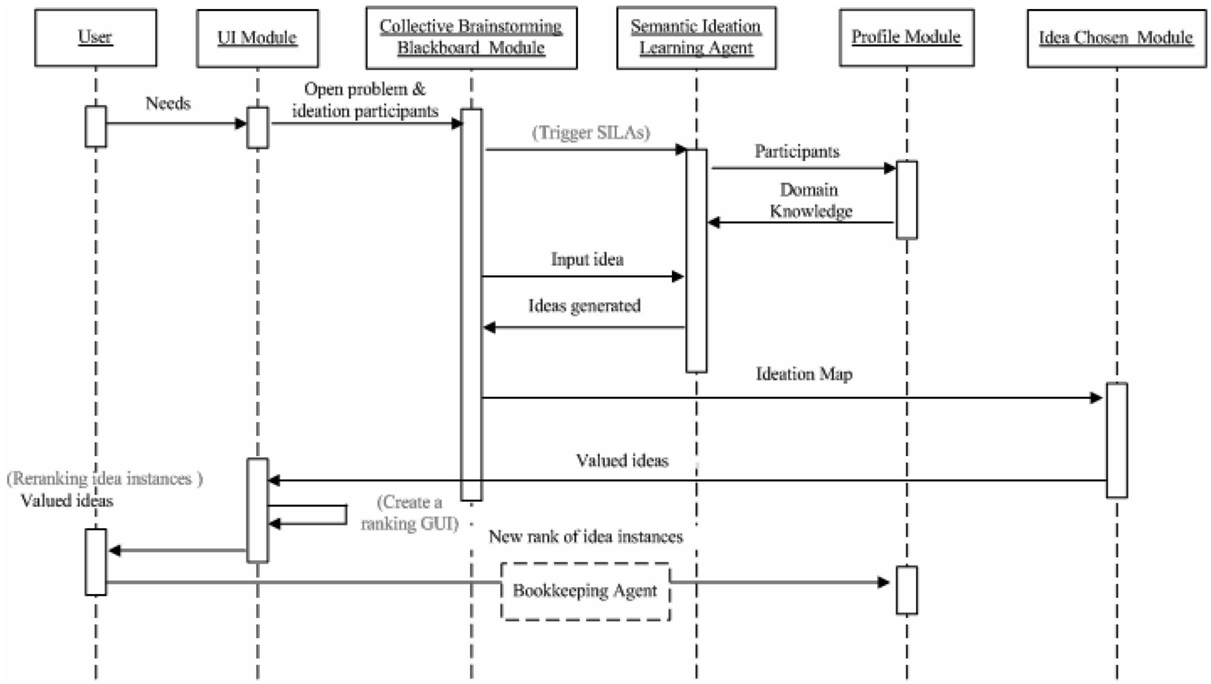


Fig. 2. Interactions between the components of CBDS.

3. Bookkeeping Agent. This forwards valued ideas to every session participants' Idea Knowledge Base, thus increasing the number of instances in each participant's Idea Knowledge Base. Accordingly, clients can enhance their domain knowledge with each round of ideation.
4. Collective Brainstorming Blackboard. In conventional brainstorming, a blackboard is prepared for participants to depict and share their creative ideas. The Collective Brainstorming Blackboard acts as the brainstorming platform. The Collective Brainstorming Blackboard receives system parameters *Initial Idea* and *Clients* from the Open Problem and Participants Component, then spontaneously initializes each client's SILA, and builds a communication platform to provide an environment in which SILAs can learn and share their knowledge. The objective of this module is to build a tree-like ideation map comprising creative ideas generated by SILAs for use by the Idea-Chosen Module (which selects qualified ideas, called *Valued Ideas*, from the ideation map).
5. SILA. A SILA is an intelligent agent that represents its client to attend the brainstorming session and manage the process of ideas association. The functions of a SILA are listed as follows:

   - receiving the *Input Idea* from the Collective Brainstorming Blackboard,
   - accessing a client's domain knowledge from Personal Data Manger Component,
   - creating a creative idea based on its inference engine, and
   - returning creative ideas to the Collective Brainstorming Blackboard.

   Hence, an ideation map is gradually constructed by repeated interactions between the Collective Brainstorming Blackboard and SILAs.
6. Idea Chosen Module. The Collective Brainstorming Blackboard assigns a numeric value, called the *Idea Chosen Indicator (ICI)*, for every creative idea on the ideation map when constructing the ideation map. Accordingly, the Idea-Chosen Module can perform a valued idea selection according to a user-set criterion after a brainstorming process finishes. For instance, a creative idea is selected as a valued idea if its *Idea Chosen Value (IEV)* is over a particular bound.

The interactions between the system components can then be described in terms of the iCare Project domain to help understand how CBDS assists in recommending innovated services tailored to the elderly at home. When a user requires a service, the UI Module treats the contextual need for the service as the open problem and assigns the session participants as the user's remote family members (that is, the clients). SILAs that represent the clients are then triggered to engage an e-brainstorming session based on every individual participant's knowledge of relevant e-services (obtained from the Profile Module) and its association capabilities. An ideation map (held in the Collective Brainstorming Blackboard) consisting of the ideas generated can then be collectively constructed and assessed using the Idea Chosen Module based on the level of interest in the ideas generated. Meanwhile, using Bookkeeping Agents, the knowledge of SILAs can also be learned and evolved with the feedback (that is, ranking of the value ideas) collected from the clients, and their Idea Knowledge Base can also be updated.

The core of the CBDS system includes the Collective Brainstorming Blackboard, SILA, the Idea Chosen Module, and the instance representation of Ideation Knowledge

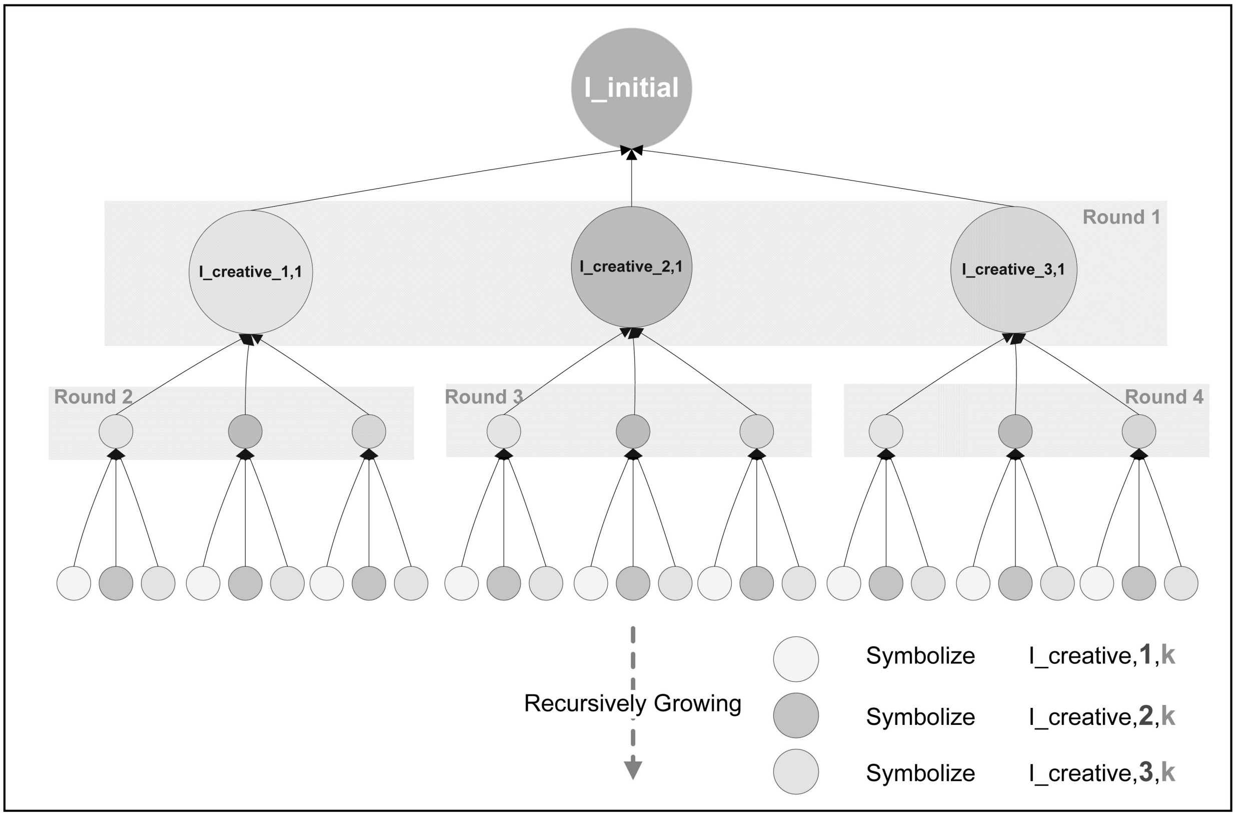


Fig. 3. Ideation Map (for example, three given clients marked with three different colors involved in the process of the map construction).

Base. These components are described in detail in the following to promote understanding of the system design.

4.1 Collective Brainstorming Blackboard

Because the aim of this study is to construct a map of creative ideas generated by SILAs and to provide an environment in which SILAs can learn and share their knowledge, an idea generation protocol is adopted to facilitate the progressive construction of a tree-like idea map. Once the Collective Brainstorming Blackboard receives the system parameters *Initial Idea* and *Clients* from the Open Problem and Participants Component, the Collective Brainstorming Blackboard triggers each client's SILA (such as client Rj with its SILA *SILA-j*) to perform the tasks detailed as follows: 1) perform an association with respect to the *Initial Idea*, 2) generate a creative idea, and 3) return the creative idea to the Collective Brainstorming Blackboard. The top level of ideas of the map is constructed in the first session, called the Round 1 session. These tasks are recursively performed for each idea created, unfolding the next level of ideas of the map in a Round i session. This process continues until a termination condition is satisfied.

Fig. 3 displays the generation of the tree-like ideation map, in which the processes of all SILAs (performing the associations with respect to a given idea and then generating their creative ideas) is termed an *Ideation Round* (denoted by the pink areas in Fig. 2). Hence, the ideation map can progressively be constructed through many ideation rounds.

That is, each ideation round has an *Input Idea*, which is regarded as SILAs' association target. For instance, the *Initial Idea* is the *Input Idea* at ideation round 1, and the creative idea generated by *SILA1* in ideation round 1 (symbolized as *I_creative,1,1*) is the *Input Idea* at ideation round 2. The objective of this map construction protocol is to achieve the maximum system creativity by forcing all SILAs to perform associations with regard to every creative idea generated (if possible).

4.2 Semantic Ideation Learning Agent

To equip a SILA with decision-making and experience-learning capabilities, this study utilizes a Reinforcement Learning method based on *Q-Learning* [21] to design SILA's inference engine, together with the capability of semantic ideation association. The Q-learning algorithm estimates the value of each state-action pair $Q(s, a)$, which are defined as the expected discounted sum of future payoffs computed by taking action a from state s and following an optimal policy thereafter. Once these values have been learned, the optimal action from any state is that with the highest Q-value (because Q-learning is known to converge when the function to be learned is stationary).

The objective of the SILA inference engine is to maximize the total long-run accumulated reward from the Collective Brainstorming Blackboard at each ideation round. The process of a SILA's decision model is described as follows:

1. At every ideation round k, SILA-j receives a state variable S_k and the *Input Idea* of ideation round k from the Collective Brainstorming Blackboard. These values are represented as $I.input$, k.
2. SILA-j generates a creative idea by referring to its client's Idea Knowledge Base and selecting an optimal association action a_k according to its Inference Engine, which is symbolized as *I.creative,j,k*.

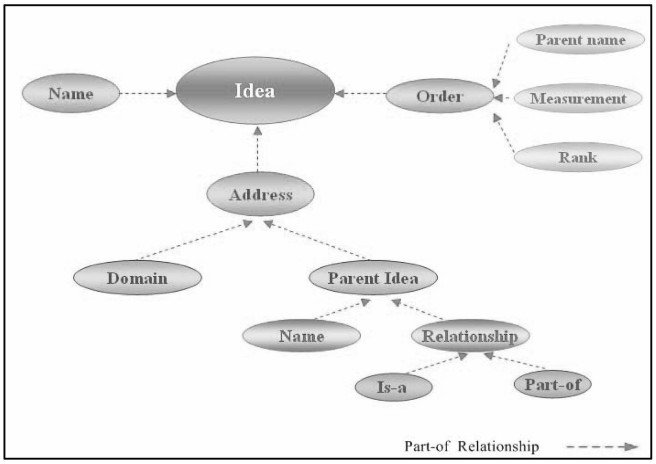


Fig. 4. Idea Ontology.

3. After receiving *I.creative,j,k*, the Collective Brainstorming Blackboard then generates a reward r_k, which indicates the learned experience of executing association action a_k and sends it to SILA-j.
4. After all SILAs execute step 2, the next ideation round $k+1$ is initiated, and SILA-j arrives in a new state S_{k+1} so as to iteratively execute step 2.

As described above, the Idea Knowledge Base and Inference Engine are the core components of SILA. These two components are described in detail next.

Idea Knowledge Base. This study employs a straightforward mechanism that facilitates intelligent agents to share their ideas. In order to reach the end, a common conception and definition of an *Idea* (that is, *Idea Ontology*) has to be shared between agents so that the agents can share with each other any *Idea Instance* (that is, a specific description of the idea ontology). Fig. 3 illustrates the *Idea Ontology* representing that the composition of an idea instance is composed. This representation can also facilitate the reasoning of the inference engine in SILAs. The Idea Knowledge Base subsequently applies the *Idea Ontology* and enfolds a collection of idea instances of different domains to denote a client's knowledge, as exemplified in Fig. 4.

As illustrated in Fig. 4, an idea instance mainly possesses three items of information:

- *Name.* This is the name of the idea instance.
- *Address.* This comprises the domain of the idea instance, the name of the parent instance of the idea instance, and the relationship between the idea instance and its parent. For simplicity, two of the most common ontology relationships, the Is-a relationship and the Part-of relationship, are adopted to represent the relationships among idea instances.
- *Order.* Within the inference of Contrast Association, an idea instance is compared with its sibling instances with the same parent instance (if of the Is-a relationship). Order information then comprises the information of the idea instance's parent instance name (of the Is-a relationship), the measurement adopted for the comparison, and the ranking of the idea instance among its sibling instances under the measurement. Definition 1 then defines the elements of instance information.

Definition 1 (Instance).

$$\text{Instance\_}\mathbf{Name} = \{\mathbf{Address}, \mathbf{Order}\}$$

$$\begin{aligned} \mathbf{Address} &= \text{a set of value elements as} \\ & \quad\ Domain\_ParentName(Relationship), \\ \mathbf{Order} &= \text{a set of value elements as} \\ & \quad\ Parentname\_Measurement(Rank) \end{aligned}$$

Therein

- **Address** *could be Multivalue and*
- **Order** *could be Null Value or Multivalue.*

A client's Idea Knowledge Base comprises an Idea Ontology and the client's knowledge of different domains. Every knowledge domain comprises many idea instances and the relationships between them, thus representing a client's knowledge under that specific domain. Fig. 5 depicts an example of a client's knowledge domain (transportation domain knowledge), in which each node represents an idea instance. Fig. 5 illustrates the transportation domain knowledge assumed by a client Rj, where the cognitive rank of Rj measured by *Speed* under the *Land Transport* is presumed in the following order:

1. Train,
2. Car,
3. Wagon,
4. Motorcycle, and
5. Bicycle.

Taking a Car instance as an example, its instance representation is shown as follows:

$$\text{Instance\_}\mathbf{Car} = \{ \begin{array}{ll} Transportation\_LandTransport\ (is\text{-}a), & \\ Transportation\_Garage\ (part\text{-}of), & \\ LandTransport\_Speed\ (2) & \}. \end{array}$$

Therein, *Transportation_LandTransport(is-a)* and *Transportation_Garage(part-of)* denote the address information of car instance, which means that a Car instance has two parent instances in the transportation domain. One instance is LandTransport, associated with it by an Is-a Relationship, and the other is Garage, associated by a Part-of Relationship. *LandTransport_Speed (2)* denotes the order information of the Car instance, and signifies that the instance's rank (measured by speed compared with its sibling instances) is 2.

Inference Engine. This study brings the three association capabilities of human thought and Q-learning into the design of SILA's inference engine, thus allowing SILAs to perform idea associations and generate creative ideas based on the instance information. The description of the inference engine has three parts. First, three instance associations are defined with respect to human's three association capabilities. Second, the environment state, action space, and reward function are modeled by the adoption of Q-Learning within the engine. Finally, the engine's instance association algorithm is presented. The details are then given in the following.

4.2.1 Instance Association Relationship

After combining the concepts of association and instance information, three instance association relationships are defined (Table 1) with regard to similarity, contiguity, and contrast. By nature, these relationships are heuristically defined in terms of inspecting the intuitive linkages among

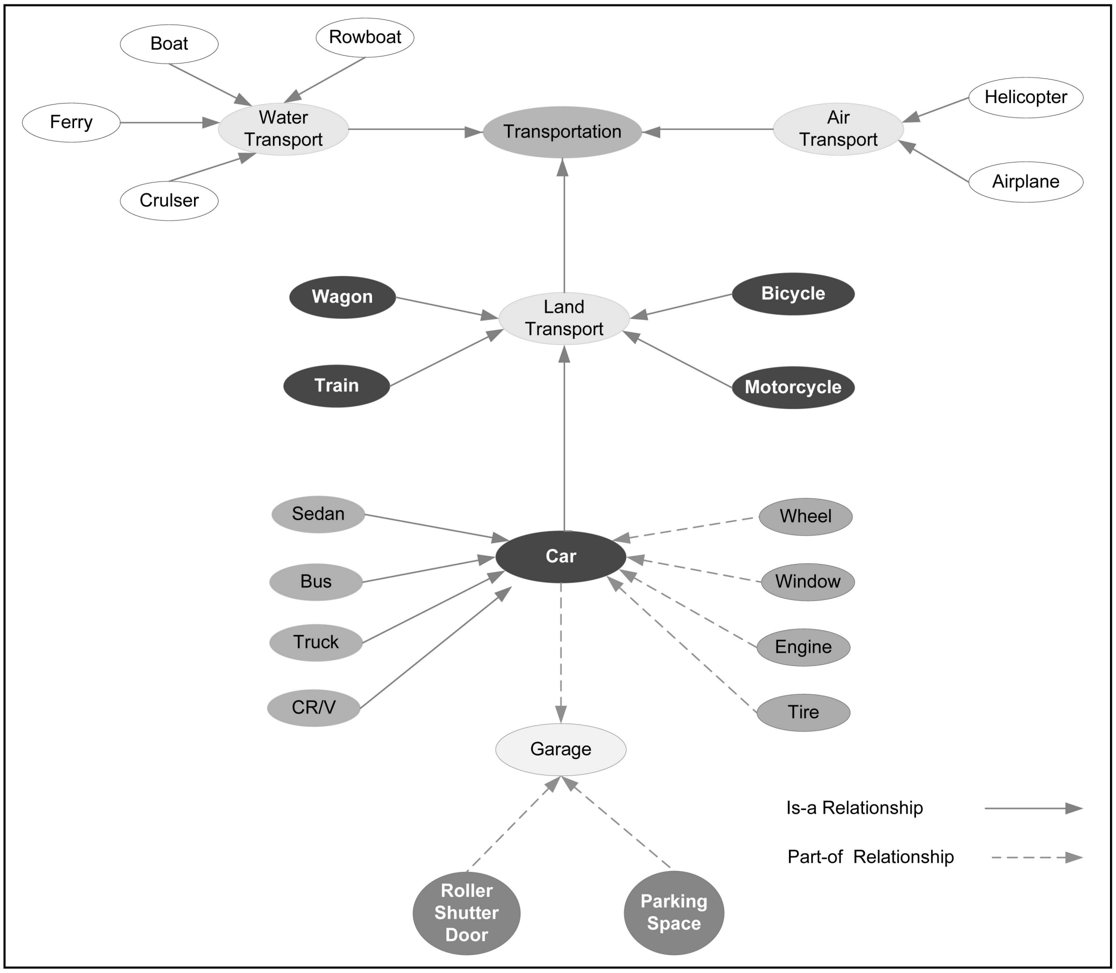


Fig. 5. An exemplar of a client's knowledge domain (transportation domain knowledge).

the three association capabilities in terms of the Is-a and Part-of relationships.

4.2.2 Semantic Ideation Learning Agent Q-Learning Modeling

Q-Learning is a form of Reinforcement learning and comprises three constituent elements, namely, environment state, agent's action, and environment reward.

Environment State. As shown in Fig. 1, a SILA interacts with the Collective Brainstorming Blackboard. A SILA receives a different environment state, namely, an *Input Idea*, at each ideation round. The environment state variable is then defined as follows:

Definition 2 (Environment State Variable). *Let S_k symbolize the state variable at an ideation round k, and*

$$S_k = I.\text{input}, k.$$

Therein,

- *k is the serial number of an ideation round.*

SILA's Action. Once S_k is received from the Collective Brainstorming Blackboard, a SILA makes a selection of the association action a_k according to the SILA's learned stationary policy $\pi^*(s_k)$, which maps a state to an action and denotes the learned experience of the SILA. Considering the car instance displayed in Fig. 4 (part of the domain knowledge of Rj) as an example, SILA-j chooses one of the following associations as its action:

1. *Similarity Association.* According to Fig. 4 and Table 1, Wagon, Train, Car, Motorcycle, and Bicycle are the sibling instances (connected with the Is-a Relationship), which are mutually linked by a similarity association relationship. The similarity association means that one of the Car instance's Is-a relationship siblings is then selected as the output. That is, considering the environment state S_k of the input idea of the Car instance, first, SILA-j determines the Is-a relationship parent instance of the Car instance from the address information, as given in the *LandTransport* instance. Second, it obtains the similarity sibling instance set of the Car instance represented as $\text{SSI\_Car} = \{\text{Wagon}, \text{Train}, \text{Bicycle}, \text{Motorcycle}\}$ by retrieving all instance information under the transportation domain. Finally, it randomly chooses an instance from SSI as the result of similarity association symbolized as *I.creative,j,k*.
2. *Contiguity Association.* According to Fig. 4 and Table 1, Car, Roller Shutter Door, and Parking Space are the sibling instances (connected with the Part-of Relationship), which are mutually linked by contiguity association relationships. Due to the contiguity association, one of the Car instance's Part-of siblings

TABLE 1
Instance Association Relationships

Instance Association Relationship	Definition
Similarity Association Relationship	If sibling instances are of the same parent instance with the Is-a relationship, they are mutually connected by similarity association relationship.
Contiguity Association Relationship	If sibling instances are of the same parent instance with the Part-of relationship, they are mutually connected by contiguity association relationship.
Contrast Association Relationship	If sibling instances are of the same parent instance with the Is-a relationship (together with the order information within their instance information), one sibling instance (the farthest) can then be identified being connected by contrast association relationship with respect to a given idea instance.

is then chosen as the output. That is, considering the environment state S_k of the input idea of the Car instance, first, SILA-j determines the Part-of relationship parent instance of the Car instance through its address information, that is, the *Garage* instance. Second, it obtains the contiguity sibling instance set of the Car instance, denoted as $\mathrm{CSI\_Car} = \{\mathrm{Roller\ Shutter\ Door, Parking\ Space}\}$ by retrieving all instance information under the transportation domain. Finally, it randomly chooses an instance from CSI as the result of the contiguity association symbolized as *I.creative,j,k*.

3. *Contrast Association.* According to the contrast association relationship defined in Table 1, achieving the contrast association involves two steps. Considering the environment state S_k of the input idea of the Car instance, first, SILA-j determines the similarity sibling instance set of the Car instance, measured and ranked using a common measurement represented as $\mathrm{SSI\_Car\_}Speed = \{\mathrm{Train, Car, Wagon,\ \ Motorcycle, Bicycle}\}$. Second, SILA-j executes the Contrast Association Algorithm (illustrated as follows) in order to obtain a contrast sibling instance of the Car instance. This instance is considered as the result of the contrast association and is represented as *I.creative,j,k*.

Function Contrast_Association $(\mathrm{SSI\_}S_k\mathrm{\_}Measurement)$
/*Contrast association algorithm*/
input:
$\mathrm{SSI\_}S_k\mathrm{\_}Measurement$: the similarity sibling instance set of the S_k with the same measurement
variable:
R: the rank of the S_k in $\mathrm{SSI\_}S_k\mathrm{\_}Measurement$
T: the total number of the instances in $\mathrm{SSI\_}S_k\mathrm{\_}Measurement$
begin
if $\mathrm{R} <= 0.5 * \mathrm{T}$ **then**
return $\mathrm{SSI\_}S_k\mathrm{\_}Measurement(\mathrm{T})$
else
return $\mathrm{SSI\_}S_k\mathrm{\_}Measurement(1)$

The rationale behind this contrast association algorithm is explained as follows:

1. Given that $\mathrm{SSI\_}Car\_Speed = \{\mathrm{Train, Car, Wagon, Motorcycle, Bicycle}\}$, the rank of the Car instance in $\mathrm{SSI\_Car\_}Speed$ is known to be 2 (that is, $\mathrm{R} = 2$), and the total number of instances in $\mathrm{SSI\_Car\_}Speed$ is 5 (that is, $\mathrm{T} = 5$).
2. The lowest ranking instance in $\mathrm{SSI\_Car\_}Speed$, that is, Bicycle, is returned according to the condition statement $(\mathrm{R} \leq 0.5 \times \mathrm{T})$. This signifies that the farthest instance from the Car instance within $\mathrm{SSI\_Car\_}Speed$ according to the speed ranking is Bicycle (that is, Bicycle is the contrast instance of the Car instance under the speed measurement).
3. Thus, the farthest instance from the Car instance between the sibling instances (connected with the Is-a Relationship) is the most contrast instance. This farthest instance, which is the result of the contrast association, is chosen as the output.

In summary, once S_k is received from the Collective Brainstorming Blackboard, SILA-j chooses OR selects one of the associations as the action a_k according to SILA-j's policy $\pi^*(s_k)$, executes the association action (that is, decides an instance according to the chosen association), and returns the instance as the creative idea. Definition 3 defines an action variable.

Definition 3 (Action Variable). *Let a_k symbolize the action that is executed by SILA-j at ideation round k, and*

$$a_k = \pi^*(s_k).$$

Therein,

- $a_k \in$ action $space = \{similarity, contiguity, contrast\}$ *and*
- $\pi^*(s_k) = \arg\max_a Q^*(s_k, a_k).$

Reward function. In a reinforcement learning model, a reward not only symbolizes the environment's assessment of an agent's action but also indicates the agent's learned experience from the action executed, which subsequently affects the agent's future decision. The proposed method uses the creative value of the creative idea generated (that is, the output idea instance *I.creative,j,k*), which is called the *IEV*, as the feedback from the environment. The calculation of *IEV* involves two factors:

1. *Number of referred sibling instances.* When handling an association action, a SILA first discovers its sibling instance set related to the association action (for example, SILA determines the similarity sibling instance set SSI when performing the similarity association) and then selects a creative idea from this sibling instance set. More sibling instances in the set indicate that the creative idea has a higher value. That is, the number of referred sibling instances is considered proportional to the creative value of the creative idea, because it indicates the scope of instances under exploration for ideation.
2. *Radical level of association action.* The contrast association is generally more radical (unintuitive) than the similarity and contiguity associations in human thinking. Consequently, the creative value of an idea instance generated by the contrast association should be greater than that generated by the similarity and contiguity associations. For simplicity, this study simply requires that the radical level of the contrast association be twice the similarity or contiguity associations. Definition 4 defines the reward function based on these two factors.

Definition 4 (Reward Function).

$$r_k = \mathrm{N} * \mathrm{A}.$$

Therein,

- r_k *symbolizes the creative value of the* I.creative,j,k.
- *A symbolizes the way of association to generate* I.creative,j,k *adopted by SILA-j, and*

$$\begin{aligned} \mathrm{A} &= 1, \text{when} \quad a_k = \text{Similarity or Contiguity},\\ \mathrm{A} &= 2, \text{when} \quad a_k = \text{Contrast}. \end{aligned}$$

- *N symbolizes the number of referred sibling instances.*

That is, we measure the creative level of an idea instance according to Definition 4 (in which the creative value of an idea is the type of association (similarity, contiguity, or contrast) times the number of the idea instance's siblings. The rationale behind this measurement is twofold:

1. From the Bounded Ideation Theory, it is implied that idea quantity could be considered as the dominant measure of e-brainstorming effectiveness when adopting an ideation protocol that resolves the problems associated with the three ideation boundaries (understanding boundary, cognitive boundary, and endurance boundary). That is, the boundaries of understanding, cognitive, and endurance alleviated by the ideation protocol address the aspects of productively serving some purpose and making changes for creativity. In this paper, serving some purpose is resolved through the task-learning capability in the agents, and making changes is then realized through the automated ideation protocol and the measurement defined in Definition 4.
2. In the ideation protocol, the number of an idea instance's siblings is related to the scope of instances to be further explored for creativity, whereas the type of association impacts the degree of changes wanted. When we refer to change within the definition of creativity, we refer to situations in which an explicit attempt is being made to bring an idea into being, which has some degree of novelty (for example, unintuition). Among the associations considered in this paper, the contrast association is viewed as the most unintuitive one.

4.2.3 *Semantic Ideation Learning Agent Instance Association Algorithm*

The instance association algorithm based on Q-Learning is presented below. The algorithm is based on the concept that the optimal action from any state is that with the highest Q-value. SILA receives the input instance of ideation around k, $I.input$, k, and views $input$, k as the state variable s_k. SILA determines a_k from the largest Q-function $Q^*(s_k, a_k)$. SILA executes a_k and generates a creative idea, namely, *I.creative,j,k.* The Collective Brainstorming Blackboard computes the creative value of the *I.creative,j,k*, represented as r_k. SILA then updates the original $Q^*(s_k, a_k)$ as the learned experience.

Function Instance_Association (I.input,k) **return** I.creative,j,k **/* Instance Association Algorithm*/**
input:
I.input,k: the input instance of the ideation round k
variable:
s_k: the state of the ideation round k
a_k: the action determined by policy $\pi^*(s_k)$ at ideation round k
r_k: the numerical reward of the a_k
s'_k: the resulting state after executed a_k
begin
$s_k = \text{I.input, k}$
$a_k = \arg\max_a Q^*(s_k, a_k)$
Execute a_k **and generate** an I.creative,j,k
Observe one-step reward r_k and $s'_k = \text{I.creative, j, k}$
Update
$Q^*(s_k, a_k) := (1-\alpha)Q^*(s_k, a_k) + \alpha[r_k + \max_{a'} Q^*(s'_k, a'_k)]$
return I.creative,j,k

4.3 Idea-Chosen Module

After completing the ideation map construction process, the Collective Brainstorming Blackboard delivers the ideation map to the Idea-Chosen Module. Every creative idea *I.creative,j,k* on the ideation map is assigned an ICI *ICI,j,k* (previously defined as r_k). A creative idea *I.creative,j,k* is viewed as a valued idea if its *ICI,j,k* value is greater than a user-defined bound. Alternatively, the ideas are sorted based on their ICI, and the top n (a user-specified number) of ideas are regarded as valued ideas. After filtering the ideas, the Idea-Chosen Module can then deliver the valued-idea set

e-services / SILA	Domestic-Travel Arrangement	e-Pet	Immediate-Family StateReport	Home-Movie	Relatives and Friends Connection Service	Interactive On-Line Treatment	TV-Show Recommendation	Warming Music
Son	V	V	V	V				
Daughter			V	V	V	V		
Family Doctor					V	V	V	V
SILA – 4	V	V			V	V		
SILA – 5	V	V					V	V
SILA – 6			V	V		V	V	
SILA –7	V		V		V		V	
SILA – 8	V		V			V		V
SILA - 9	V			V	V		V	
SILA -10		V	V		V			V

Fig. 6. The mapping between SILAs and their knowledge of available mental-needs services.

and the ideation map to the Valued-Notification Component to complete the entire decision process of CBDS. The Idea Selection algorithm is given as follows:

Function Idea_Chosen (quantity) **return** Valued_Ideas[]
input:
quantity: the wanted quantity of the valued ideas
variable:
I.creative.j,k: the creative idea that is created by Rj at ideation round k.
ICI,j,k: the ICI of I.creative,j,k
Sorted_Ideas[]: the set of sorted creative ideas in the decreasing order
Sorted_Ideas[i]: the i th creative idea in Sorted_Ideas[] ordered by ICI
Valued_Ideas[]: the set of the valued ideas
begin
for each I.creative,j,k **sort by** ICI,j,k and **stored into** Sorted_Ideas[]
if i $\leq$ quantity **then**
Valued_Idea[] ← Sorted_Ideas[i]
return Valued_Ideas[]

5 Application and Evaluation

The proposed agent-based e-brainstorming mechanism was integrated into the iCare Project [9] to represent certain participants engaging in an idea creation for recommending innovative care services.

iCare aims at providing quality e-services to the elderly people anywhere and anytime by using an iCare home portal. Conversely, existing services for the elderly (whether based on healthcare or e-Care) are mostly oriented to clinical gerontology (for example, exercise technology and sensor technology) or the neuropsychology of aging (for example, presymptomatic diagnosis of age-related cognitive decline and amelioration of age-related changes in human sensory and motor systems) [22] and neglect some quality dimensions such as community involvement, consumer participation, and continuous quality improvement.

Assessing our agent-based e-brainstorming mechanism within the service scope of iCare involves justifying the improvement in the number of ideas generated (that is, group creativity) and the diversity of ideas created for recommending innovated care services. An idea in the context of the iCare Project domain represents the recommendation of an e-service. Accordingly, the generated set of valued ideas is equivalent to the set of recommended e-services.

Without loss of generality, an exemplar of the given experiment settings is given as follows:

1. a universe of eight e-services (that is, possible ideas of services provisioned, as shown in the top row of Fig. 6) for mental needs under consideration,
2. as displayed in the leftmost column of Fig. 6, up to 10 possible clients (that is, their respective SILAs represented by Son, Daughter, ..., SILA-10) involved in e-brainstorming, each embodying its own knowledge of the domain of mental needs (simply represented by the correspondent marks made with respect to those e-services),
3. a benchmark Greedy mechanism, which randomly chooses an e-service based on its existing knowledge of relevant domains, for example, mental-needs domain, in order to recommend services,
4. a set of parameter values (as listed in Table 2) for inspecting the mechanism's performance, measured in terms of the metrics given in Definition 5 (Average Service Types and Service Diversity Rate), and
5. a user interface, as displayed in Fig. 7.

Definition 5 (Performance metrics).
Average Service types $= \sum_{i=1}^{N} t_i / N$
Service Diversity Rate $=$ (Average Service Types$/T) * 100\%$

- $N =$ total number of experiment times,
- $t_i =$ number of Service Types generated from the ith experiment, *and*
- $T =$ number of available e-services.

TABLE 2
Experiment Parameter Settings

Parameter	Default	Meaning
N	30	Total number of experiments
Initial Idea	Random	Random choice out of the relevant domain knowledge of e-services as shown in Figure 6
Clients	3	Total number of clients involved in the e-brainstorming
	5	
	10	
Ideation Rounds	1	Number of ideation rounds developed
	4	
	13	
α	0.8	Learning rate used in Q-Learning

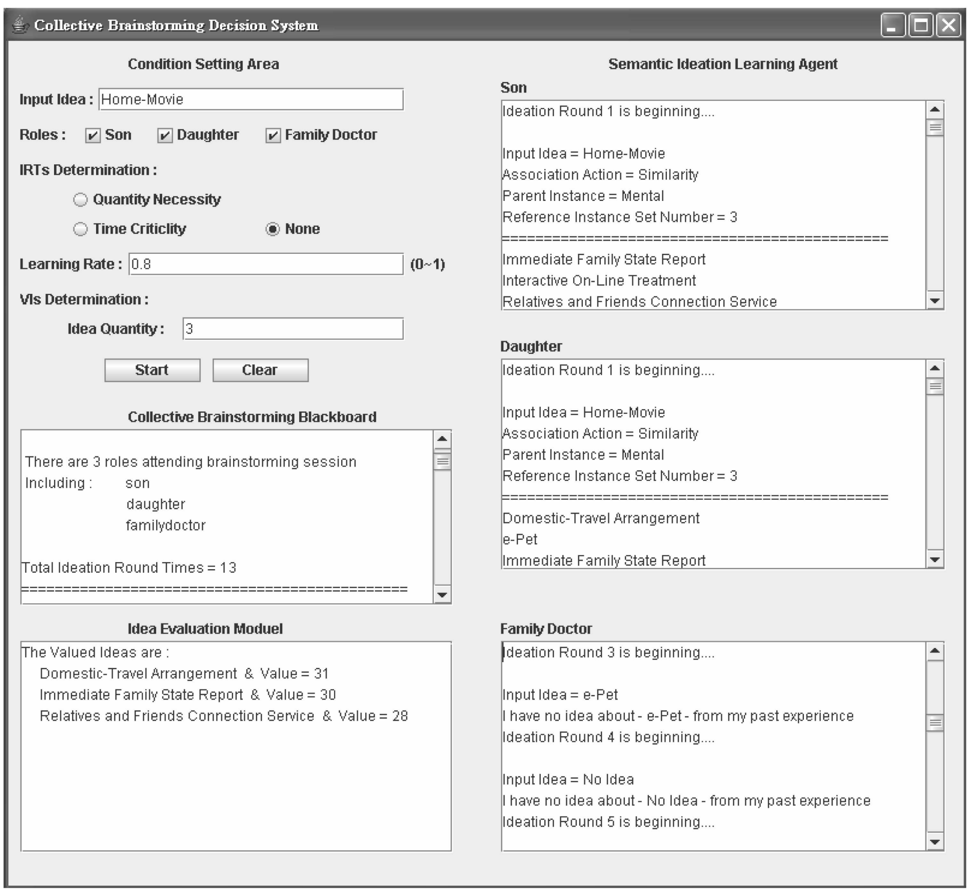


Fig. 7. CBDS system's user interface.

Table 3 and Fig. 8 reveal that CBDS indeed improves in the number of ideas generated (that is, Average Service Types) and the diversity of ideas generated (that is, Service Diversity Rate), enabling the objective of innovated care service recommendation to be realized within the service scope of iCare:

- In Table 3a, the CBDS's performance does not take SILAs' knowledge learning capabilities into account (that is, without the function of Bookkeeping Agent that forwards valued ideas to every session participants' Idea Knowledge Base so as to expand their domain knowledge as ideation rounds go by). The CBDS exhibits performance improvements of 10 percent to 33 percent (with respect to different numbers of participants involved) in terms of both Average Service Types and Service Diversity Rate, as compared with the greedy approach.

TABLE 3
CBDS Performance Results and Comparison

Decision Model		Clients = 3	Clients = 5	Clients = 10
Greedy Model	$\sum^{N} t_i$	83	118	182
	Average Service Types	2.77	3.93	6.07
	Service Diversity Rate	34.58 %	49.17 %	75.83 %
CBDS Model	$\sum^{N} t_i$	111	148	200
	Average Service Types	3.7	4.93	6.67
	Service Diversity Rate	46.25 %	61.67 %	83.33 %

(a)

Metrics	with knowledge learning	VIQ = 1	VIQ = 2	VIQ = 3
$\sum^{N} t_i$	111	144	153	182
Average Service Types	3.7	4.8	5.1	6.07
Service Diversity Rate	46.25 %	60%	63.75%	75.8%

(b)

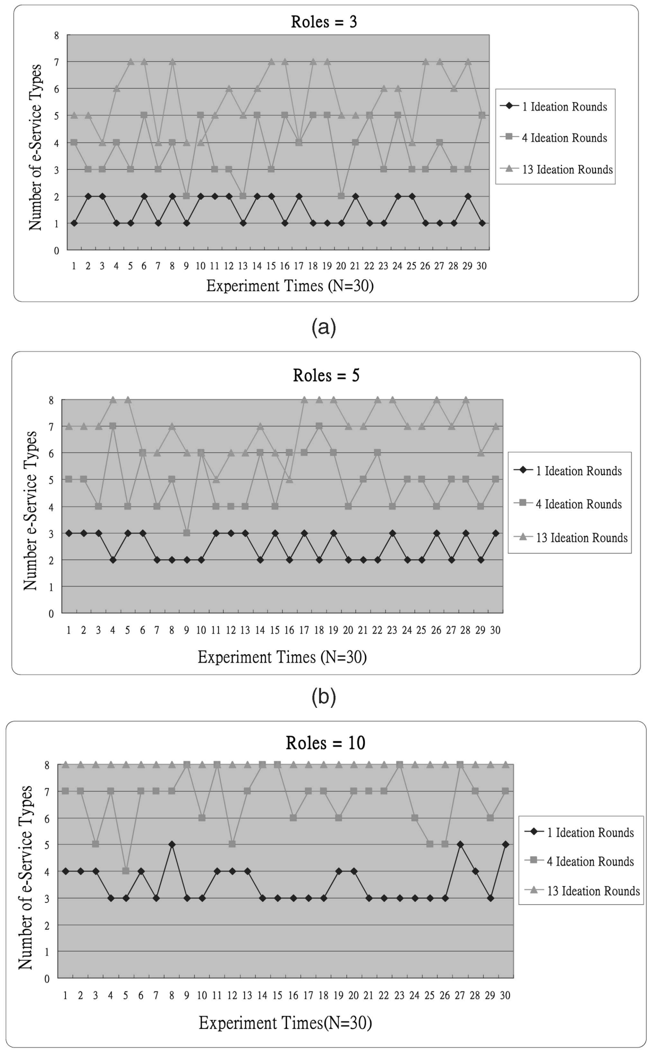
Decision Model	Clients = 3	Clients = 5	Clients = 10
Greedy Model	34.58 %	49.17 %	75.83 %
CBDS Model – 1 Ideation Rounds (i.e., not yet brainstorming learning)	18.33 %	36.25 %	44.17 %
CBDS Model – 4 Ideation Rounds	46.25 %	70 %	83.33 %
CBDS Model –13 Ideation Rounds	70.83 %	96.25 %	100 %

(c)

(a) CBDS performance results benchmarked with those of the Greedy Approach (if SILAs are without the knowledge-learning capabilities through Ideation Rounds). (b) CBDS performance results with respective VIQ Value (if SILAs are with the knowledge-learning capabilities through Ideation Rounds for the case of clients equal to 3). (c) Performance comparison in terms of Service Diversity Rate

- Table 3b indicates that the knowledge learning capabilities of SILAs lead to significant performance improvements (for example, for the case of three participants involved in the ideation session). These improvements vary according to the Valued Idea Quantity (VIQ). A VIQ is a specified number of new idea instances added into the Idea Knowledge Base. A larger VIQ indicates a larger performance improvement in CBDS.
- Table 3c indicates that the rise in the Service Diversity Rate of the CBDS is proportional to the number of participants involved (that is, Clients) and the number of ideation rounds progressed (that is, Ideation Rounds).
- Fig. 8 reveals that the quantity of Average Service Size is proportional to the numbers of Clients and ideation rounds in an e-brainstorming session.
- The preliminary results in Table 3 and Fig. 8 show that SILA can learn to understand a task (in terms of the rewarding and learning processes of Q-Learning), adopt external stimuli without restrictions in the working memory (in terms of a VIQ in each ideation session), and does not suffer from attention exhaustion (in terms of ideation rounds in every ideation session). That is, the experimental results show that the proposed agent-based ideation architecture and inference mechanism work well.

The rewarding and learning processes of Q-Learning used in SILAs can also be assessed by examining the relative service values of the recommended service ideas. The service values of the service ideas generated by SILA-Son were examined in this study. A service value refers to the expected discounted sum of future payoffs/rewards obtained by taking the action of the service idea from the state of the assumed input service idea of Home-Movie, considering the reward based on the number of idea



(c)

Fig. 8. The number of service types engendered varies with the forms of e-brainstorming sessions (of three different numbers of ideation rounds required) and the number clients involved. (a) Three clients. (b) Five clients. (c) Ten clients.

candidates and the radical level of the service ideas. This example can also act as a convincing scenario of enhanced e-brainstorming enabled by the proposed agent-based ideation architecture and inference mechanism.

Fig. 9 displays the case where the function of Bookkeeping is disabled so that the ideation knowledge of SILAs remains intact throughout the ideation session. This figure indicates a positive progression in the values of the services embodied, revealing that the e-brainstorming process produced a positive learning experience. The ranking order of strength values of the service ideas obtained from the input idea of Home-Movie service in the 17th experiment of SILA-Son were e-Pet(26), Domestic-Travel Arrangement(24), and Immediate Family-Status Report(21). This rank ordering was applied for the set of service ideas presented to the CBDS. That is, when thinking about something creative but relevant to Home-Movie (that is, a feeling oriented toward home and family), e-Pet or travel arrangement with the family members are more attractive ideas than a straightforward status report of the family members (based on the SILA-Son's knowledge of the four e-services, as indicated in Fig. 6).

In summary, the experimental results presented in Fig. 9 reveal that a SILA's positive learning process (powered by the rewarding and learning processes of Q-Learning) in terms of the relative strengths of the values of the service ideas generated by the SILA (in which services with higher service values are more creative and of high priorities to be recommended).

6 Conclusion

This paper presents the use of semantic ideation agents (SILAs) in the e-brainstorming process in order to reach automatic collective decisions by e-brainstorming. In this process, SILAs collaborate with a CBDS e-brainstorming system architecture. SILA can learn to understand the task and utilize external stimuli without restrictions in the working memory or attention span. CBDS is the ideation architecture and environment, with which SILAs can learn and share knowledge.

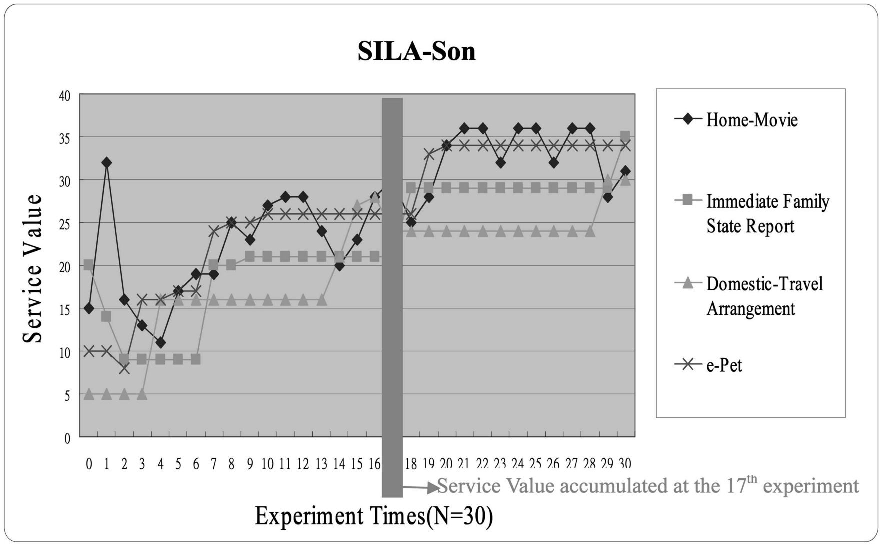


Fig. 9. The values of the service ideas embodied by SILA-Son.

The proposed method advances the current state of the art of e-brainstorming by developing SILAs that proactively engage in idea association instead of just passively supporting brainstorming sessions. Although a big gap still exists between artificial brainstorming and creative human brainstorming, this study advances existing e-brainstorming research by crossing the three key boundaries of the human ideation capability (understanding, cognition, and endurance). We believe that the proposed agent-based e-brainstorming system improves e-service recommendation and delivery by creating a novel reasoning process for recommender systems, focusing on producing creative recommendations (as exemplified in the iCare Project).

However, the proposed mechanism still has limitations, owing to the confined scopes of SILA's association capabilities and ideation ontologies, and the rigidity of the protocol for ideation map construction. Future work will incorporate new association techniques and flexible agent ideation protocols and explore different semantic ideation ontologies and idea evaluation systems. Additionally, the dynamic evolution of ideation ontologies and possible scopes of future applications will be addressed.

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