Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Niche of Idea Activations as Source of Social Creativity: a Finding from Innovation Game

Yukio Ohsawa, *Member, IEEE,* Yoko Nishihara, *Non-member*

***Abstract*— By mining and looking at the relations between pieces of knowledge, the talent of human to create an idea from a combination of knowledge comes to be elevated. In this paper, the Innovation Game we have been presenting since last year is introduced as an environment for the communication to elevate this talent. The players called innovators present ideas created from combining prepared basic ideas, and sell the ideas to each other and their stocks to investors. As a result, the values of ideas are evaluated, to reveal latent opportunities in the market. Here we present experimental results showing the niche, i.e., the space between clusters of already used or newly invented ideas of business, tends to enable players to create ideas/products of which the quality can be highly evaluated by the human society.**

I. Introduction: The Process to Value-Cognition

Let us start from our example with a textile firm in 2002, which we presented previously [1]. Among other sponsors of the author, the company had been especially strongly seeking to develop new products, i.e., new kinds of textile to be accepted by the market. The staffs were well aware that the three major parts of their market were relevant to textiles for (*Submarket 1*) business suits, (*Submarket 2*) business under-wear, and (*Submarket 3*) casual wear. Typical designs of these clothes are shown in Fig. 1.

Although they had a mature market of these kinds of products, they also desired to develop further new markets starting from a niche product i.e., a product which may be rare for the time being but can expand the company's market. For doing this, they started from data on product exhibitions where customers representing apparel companies picked samples they prefer and left the list of those samples. Previously, this list had been used only as an order card on which to send samples to the ordering customers. However, the staffs of the textile company were feeling the same list, if filed into an electronic dataset, may be a source of ideas for designing new products. They visualized the data using decision trees, correspondence analysis, etc, but still looked for the best tool for achieving their goal. After all, they reached KeyGraph [2,3], which shows (1) *clusters of frequent items in the data,* i.e., item-sets which are ordered frequently by the same customers, and, (2) *items ordered rarely but appear in the same baskets as items in multiple clusters*. The figure was obtained as in Fig. 2, where the black nodes linked by black lines show the clusters of (1) mentioned above, and the red nodes and the red lines show items of (2) above and their co-occurrence with items in the clusters, respectively.

Manuscript received March 30, 2009.
Yukio Ohsawa, Dr. is an Associate Professor, and Yoko Nishihara, Dr. is an Assistant Professor, in the Dept. Systems Innovation, School of Engineering, The University of Tokyo, 113-8656 Tokyo, Japan.

Fig.1 How can we combine multidisciplinary knowledge, for satisfying the consumers/users?

In order to make it easy to interpret this figure for marketers in the company, they attached product samples as in Fig. 3. This device aided the viewers to sense the smoothness, thickness, colors, etc with their eyes and fingers. The meeting of the members in the marketing section ran as follows:

1) First, they noticed the clusters corresponding to popular item sets (clusters mentioned as in (1) above). 3 marketers who are experts of women's blouse noticed the meaningful cluster at the top of Fig. 3 corresponding to the *Submarket 3* in Fig.1, and 3 others noticed the cluster at the right of Fig. 4 corresponding to business suits as *Submarket* 3 in Fig.1. 2 others noticed the popular item in the left of the diagram, not linked to any clusters of (1) via black lines, corresponding to materials in *Submarket* 1.
2) Second, a marketer who had been working long paid attention to the relations among the three submarkets, after hearing the other marketers' opinions. Then he presented as scenario that women who daily use business wear (combination of suits and blouse) may not really like the style, but desire a change into a casual wear made of textile as in the Submarket 1 of Fig. 4.
3) Based on the scenario talked in step 2), the marketers in the team paid attention to the item between the large meta-cluster (the combination of Submarkets 2 and 3) and an item in Submarket 1. These in-between nodes are the red nodes in Fig.2, i.e., rare items as a niche between popular clusters, on which the marketers finally designed a new semi-casual cloth in which women can go both to working places and to lunch/dinner after working. As a result, the material of the red node marked a hit – 13th highest sales among their 800 products.

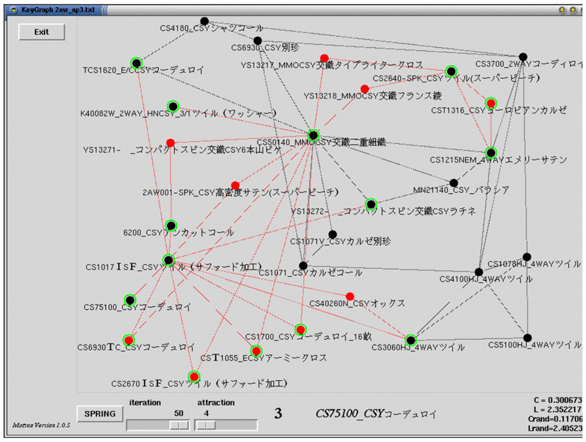

Fig.2 KeyGraph for the data on customers' preference in an event of textile exhibition

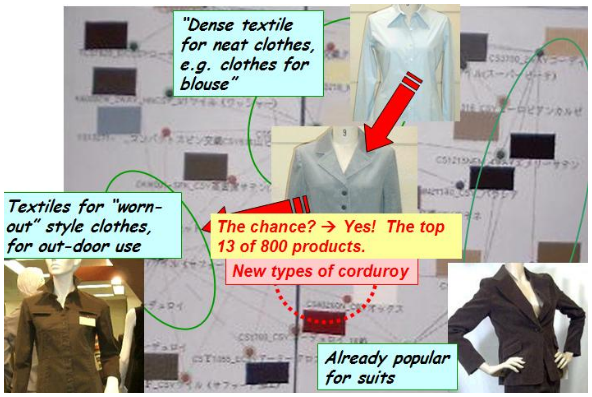

Fig.3 Marketing as value sensing has been realized with KeyGraph

This episode (see [1] for details on the technical aspect of this case) implies three important facts: First, data collected based on the users' (marketers', in this case) own sense of value, i.e., of the relation of target events to their own interest, lead them to successful marketing with the development of promising products. Second, the visualization tool provides a workplace where co-workers bring multidisciplinary expertise and combine ideas to create new business scenarios. Third, not only visualization of the raw data but also devising a new interface for showing it to suitable users, as done with attaching real textile pieces for aiding experts of textiles to think of underlying scenarios, plays a role as a support of creative decision in business.

However, although the fruits of data mining (including the visualization of patterns in data as in the example above) have been proven useful in some real business such as marketing (See [4, 5]), the current state is still far from universal utility. That is, not many users realize successful businesses using tools of data mining. This is mainly due to three reasons (1) the difficulty in acquiring the basic talents on the side of human, (2) the lack in suitable tools for assisting the overall process of knowledge discovery and decision making, (3) users' weak interest in obtaining new values. That is, most users in business tend to use no more than known and available tools based on their unchanged value criteria such as the cost of retailing, without training their sensitivity or their talents for thought and communication.

Thus, we need at least two significant leaps: (1) change human's viewpoint for catching not only transient events and situations, but also knowledge and ideas which have been existing and may embrace a latent value, (2) take care of the huge amount of information in the environment, which have not been included in data (3) develop and integrate tools for training and aiding skills for meta-cognition (cognition of one's own cognition, for noticing the latent criteria of value in the mind) of human(s) , as well as the visualization tools.

II. Innovation Game

Innovation Game is our original game-like environment for communication, where combinatorial creativity, i.e., creating a new idea from a combination of ideas, is activated. The game starts with 30 to 50 basic cards, on each of which the title, an image, and the summary of some existing knowledge of business or technology is written. The core players are called *innovators* (like innovative leaders of companies), who starts with the capital of $10. The innovator's main operation is to (1) buy a preferable number of basic cards for pre-set prices, (2) combine the cards of one's own or cards bought/borrowed from other players, to present an idea created by the combination. Other innovators may propose the presenter to start collaboration, or borrow/buy the new idea, with negotiating the dealing price. At the halting time (such as 2 hours after starting), the richest player, i.e., the player having the largest amount of money wins.

There are *investors* and *consumers* around innovators who all start from 10$ capital. Each investor buys stocks from innovators who seem to be promisingly excellent, according to the investor's own subjective sense of ideas' values, or from other investors. The investor having obtained the stock-set of the highest amount of total price at the halting time comes to be the winning investor. And, each consumer buys preferable ideas and virtually introduce them to his/her own lifestyle, for the prices fixed by negotiation with innovators. The consumer who obtained the idea-set of the highest total value (the value of an idea can be defined in various ways, e.g., the price of the idea at its last dealt time) comes to be the winning consumer.

The KeyGraph obtained from the prepared basic cards is used as the game-board of Innovation Game, as in Figure 4. Here the KeyGraph visualizes the market of ideas, showing the positions of not only existing knowledge represented by basic cards but also of latent ideas not appearing on any basic cards but may be created by combinations. This visualization came to be enabled by extending KeyGraph, in the way called Data Crystallization ([6, 7]), which shows *the black nodes and links* corresponding to basic cards organizing clusters, where each cluster embraces a common context, i.e., a set of cards sharing words in the summaries, and nodes (colored red in the real output) connecting the clusters via dotted lines. For example, a node DExx (e.g. DE25 and DE61) in Figure 4 mean that a new idea may emerge at the position by combining ideas in the (black) clusters connected to DExx. On this graph, Innovation Game goes on with the activities of innovators as:

(1) Put basic cards on corresponding black nodes, when combining the cards for creating an idea, *and*

(2) Put a "wild" card which is a colored post-it on which the player can write his own created idea, at a chosen position on the graph. Putting on a red node in the graph is recommended, but not forced. The color of the post-it corresponds to each individual innovator. For example, innovator Mr. Red may write on red post-its, whereas Mrs.Blue may write on blue ones.

The quality of a created idea is evaluated after the game by investors and consumers on criteria such as originality, utility, reality, etc. For example, the idea cards on black nodes in Figure 4, are:

"Customized education": A customized program of computer-aided education for each student

"Room of time": A room the resident can experience a longer time than the really passed time

Note that the exemplified game here was an imaginary one, i.e., where the basic ideas and innovators represented those of year 2050 when these technologies may have appeared. An idea obtained by combining the two above was "ultra-efficient education system," a system to enable students to study efficiently in the room of time on the well coordinated schedule supported by the customized education. Although the room of time may seem unrealistic, the expected utility of the new idea was evaluated highly by investors. The players of games we conducted (we organized more than 30 games so far) mention they feel their skills of communication and thought for creating socially useful knowledge has been elevated by the game. The effect for their talent acquisition by the game is being evaluated currently.

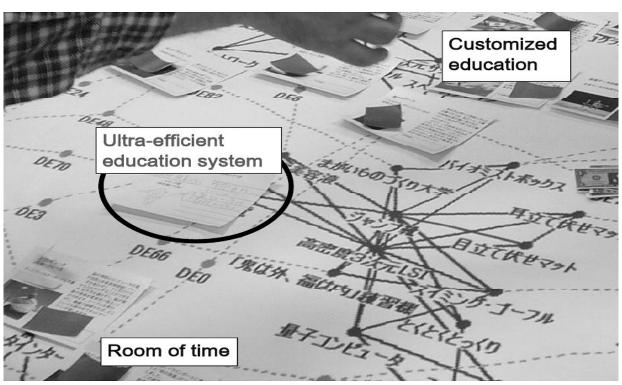

Figure 4. Innovation game on the game board, made of KeyGraph with data crystallization

III. Experimental Innovation Games

Experiment setting We have been trying Innovation Game for several kinds of players. In some games, we had all players from the School of Engineering. In other games, students from across multiple disciplines (engineering, economics, law, etc) , or business people in a company across multiple sections (research, design/ development of products, marketing, etc), joined one game. We also tried open games where students and business people joined anonymously.

In all games, the most important finding was that Innovation Game is an enjoyable environment for innovative thought rather than a workplace forced to think new ideas for the sake of the unit players belong to. This is meaningful for real application to business, because being forced to think disturbs one from introducing their tacit knowledge acquired from daily experiences, and also from extensive production of ideas about the future scenarios. Even worse, the feeling that their ideas may be reflected to their income and promotion causes a fatal negative effect, because one tends to reject others' negative comments about one's own presentation even if the comment may be helpful in improving the idea. Thus, a motivation different from being forced to think is desired in workplaces where fine fruits of innovation are desired.

In the experimental games so far, we collected such data on the behaviors of players as:

(*Data* set *1*) The video data of all games, recording the voices and the actions, including idea presentations and buying/selling ideas and stocks.

(*Data set 2*) The score of each idea: As stated above: The quality of created ideas is evaluated after the game, by investors and consumers on criteria such as "originality," "social demand", "earning power," "reality".

By combining these two datasets, we can investigate the effect of communication to the quality of ideas. For example, the effect of empathetic utterances, rather than of utterances for negotiations, to the originality of created ideas has been detected. However, such a finding is not satisfactory for convincing us of the fundamental mechanism of creations in the game, although it is interesting from the view point of ethics. In this paper, we present the source of highly valued ideas from the aspect of the interaction of ideas, as we found in the industrial example in Section II. Reflecting this aim, we made a rule that the players must manually write down the following information in each card of a created idea:

(*Data set 3*) The idea created, hand-written in text. During the period of a game, each idea was marked from 'A,' 'B,' 'C,' etc, corresponding to the order of presentations

(*Data set 4*) The list of ideas or knowledge (in the basic cards) combined in creating the idea in (*Data set 3*)

We conducted five games, where innovators and consumers joined as players. Each game was continued 120 minutes, after which the scores of players were computed. The score of consumers were defined by the average score of "originality," "social demand", "earning power," "reality" in order to have consumers consider the social value of ideas in the emotional excitation of the game. Such factors as cost and business risks were encouraged to be counted in the factor of reality.

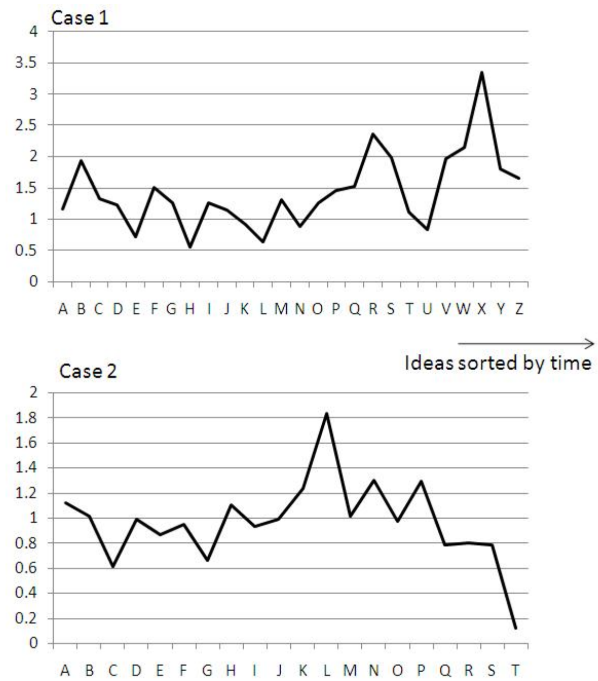

Figure 6. The changes of scores with time presenting ideas

Results I: The time-sequence of the quality of presented ideas
The simplest tendency result we observed so far is that the quality of ideas tends to increase with time, as exemplified in Figure 6. This figure shows the increase in the value of *originality* * *reality*, where the originality and reality tends to change in a trade-off relationship (i.e., one increases when the other decreases) but both are necessary for realizing innovation where real contribution to the sustainable social welfare is demanded.

However, this trend of the growth in score is not always the case, and the very last few ideas as Z in Case 1 or Q, R, S, and T in case 2 are found to fade down. Thus, we focused on the temporal effect, where previously presented ideas affect to the idea created at each time during the game. That is, the increase of scores may come from the effect of previously presented ideas, and the fade at last may be hypothesized as an effect of saturation caused by the rash of ideas. Actually, the decrease trend is typically found in cases where highly scored ideas lasted throughout the gaming time.

Results II: The niche ideas
We started from a several hypotheses reflecting theories of creativity in the literature and our original experiences in chance discovery. For example, innovation comes from the combination of existing ideas according to [8, 9]. If so, all new ideas in the game are expected to satisfy the consumers who attend the game from a viewpoint considering the long-time future. Some other theories insist that ambiguous information [10] and suitable questions [11] enforces the creativity in design. We may validate such a hypothesis from the analysis of communications in Innovation Games.

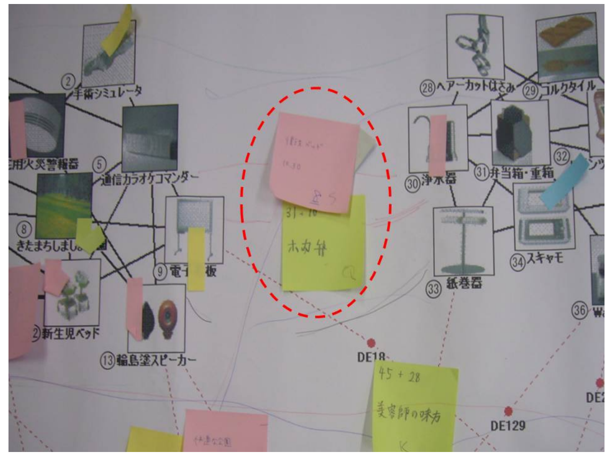

Figure 7. Free niche ideas: without connections via links in the graph

Figure 8. Connected niche ideas: with connections via links in the graph

Among these possibilities, the finding we can present here is the relevance of *idea niche* to innovation. For example, Figures 7 and 8 shows the niches of different types. In Figure 7, a created idea is put on a free space, i.e., not at any node in or between clusters which were combined for the creation. However, the clusters include other ideas which had been used previously. And, in Figure 8, a new idea is presented at a red node (via the dotted lines visualized automatically by in KeyGraph, on the data of text in basic cards), between clusters including basic cards which had been already used .

Let us call the former type of niche, i.e., an idea created at a node connecting nodes in cluster(s) including already-used basic cards, via links in the graph, a *connected niche idea*. We can observe such an idea has been created by combining ideas in those cluster, by seeing the hand-written data showing the list of ideas the player used for the creation (data 3 above). Here, a new idea created beforehand can be regarded as such a cluster. And, let us call the latter, i.e, an idea created by combining ideas in clusters not connected via links but including already-used basic cards, a *free niche idea*.

A niche can be regarded as a kind of combination of ideas for innovation as stated in the literature, but a niche here also means that the combined ideas have been used in the thought and the process of incubation of ideas have started. As in the example of Section II, the prepared mind favoring a chance can be interpreted as the experiences and thoughts before catching a new clue for creation. In [12, 13], we find theorization of making sense of a new events, on the framework of analogical reasoning.

In the following procedure, we evaluated the ideas in the six types of niche. First, in preparation before the evaluation, we had the score of each idea evaluated as in *Results I.* Then, all ideas were taken away from the game board (the graph of KeyGraph) and the created ideas were put again on the game board one by one. For each time creating an idea, Steps 1 through 3 below are processed.

Step 1 (categorization of each idea presented): Each time an idea T was created on the game board made by KeyGraph, conditions X and Y as follow are checked.

X: The extent to which the ideas combined for creating T belonged to clusters including ideas in set U, the set of ideas used by the time (2: Yes, all the combined ideas belonged, 0: No, none of the combined ideas did, 1: between 0 and 2 i.e., some but not all of the ideas combined for creating T belonged to such clusters).

Y: Whether the idea was put on an existing node/line, where it is red or black.

For the values of ideas, idea T is categorized by X and Y as: If X is 2, 1, or 0, then T is *between activated clusters (niche)*, *between partially activated clusters*, or *between newly activated clusters*, respectively. If Y is no, T is *free*. If Y is yes, then T is *connected.*

Step 2 (attach missing links): When there is no node on the game board suitable to put the created idea on, the player can put it on a free space i.e., missing any node, but should draw a new red line connecting the created idea and the clusters including the combined basic ideas.

Step 3 (cluster revision): If there are multiple clusters connected via red lines (drawn automatically or manually), and which contributed to creating the same ideas by combination of belonging ideas so far, the clusters are unified into one cluster. Thereafter, thus revised clusters are used for categorization of ideas.

As a result, all presented ideas in the experimental 5 games were classified into the six classes, corresponding to the 3 values of X and 2 values of Y respectively. Then, for all the ideas in each class, the evaluated scores were checked and the rate of 10 and 5 highest-score ideas for each game was counted in each class respectively. The results are shown in Tables 1 and 2. Here, we find the "between activated clusters" i.e., the niches, are shown to include the highest-score ideas although the standard deviation is still large due to the small number of games of which we recorded all data (Data 1 through 4). The difference between the free and the connected niches are small (compare the difference of average values and the standard deviation, although we skip t-tests here), especially for the 10 highest-score ideas. We find more significant difference for 5 highest-score ideas, although we should collect data for larger number of games, which should take an additional half year under the similar experimental setting. On the other hand, the standard deviation for the free niche is significantly larger than for the connected niches, as shown in the two tables.

Table 1. The rate of the 10 highest scored ideas, in two kinds of niche (left most) ideas and others: *Average (standard deviation)*

	Between activated clusters (niche)	*Between partially activated clusters*	*Between newly activated clusters*
Free	*.51 (.30)*	*.18 (.27).*	*.1(.22)*
Connected	*.45 (.19)*	*.27 (.43)*	*0 (0)*

Table 2. The rate of the 5 highest scored ideas, in two kinds of niche (left most) ideas and others: *Average (standard deviation)*

	Between activated cluster (niche)	*Between partially activated cluster*	*Between newly activated cluster*
Free	*.40 (.42)*	*.04 (.09).*	*.1(.22)*
Connected	*.26 (.15)*	*.17 (.24)*	*0 (0)*

Discussion

Summarizing Tables 1 and 2 of *Results II*, we can predict (not yet conclude, due to the small number of games):

Tendency 1: The niche ideas include the highest score (defined by *originality* reality*) at high rate.

Tendency 2: The free niche tends to include especially highly scored ideas, but the deviation is large i.e., the reliability of the ideas presented at free spaces is low.

Tendency 3: The connected niche tends to include relatively highly scored ideas, and the deviation is small i.e., the reliability of the ideas presented at nodes connected to clusters including used ideas is high.

From these tendencies, we can explain the tendencies obtained as in *Results I*. That is, the number of ideas increases on the graph with time. Accordingly, the spaces (both the free spaces and the nodes of KeyGraph) come to be surrounded by clusters including activated i.e., used or created, ideas. As a result, the players come to be forced to make niche ideas.

We can point out two more features in Figure 6. The first is the decrease in the scores of the few last ideas, especially in games where many ideas were created in the early stage. This can be explained by considering the occupation of spaces on the graph by activated ideas. The second is that the score tends to be stabilized to be high in the later stage of the game before the very last period we find fading. This can be explained by the creation of connected niche at each time, via the lines drawn manually in presenting previous ideas.

In summary, we can recommend players in the future to be patient until ideas have been created combining ideas in clusters on the graph, without expecting high scores, in the early stage. And, then, the player will be enabled to create good ideas if he/she focuses on the niches of activated ideas on the graph. Here, if the player likes a hit (especially high score), the free space between clusters including activated ideas will be recommended. On the other hand, if the player likes reliability (hedging the risk of low score), positioning ideas on nodes or lines on the graph will be better.

However, in real games in companies, where players join for making innovation for real production of products/services, it is not easy to have their patience to wait until clusters become occupied by activated ideas. Also, in some cases, they prefer to combine new ideas (in clusters missing used/activated ideas) with used ideas. In such a case, the player should learn the lesson below:

Tendency 4: The node connected to and between partially activated clusters promises more excellent ideas than a free space between partially activated clusters.

That is, if one prefers to combine ideas in clusters without activated ideas and with activated ideas, it is recommended to created an idea on a node connecting these clusters.

IV. CONCLUSIONS

In this paper, the Innovation Game we developed has been studied based on the viewpoint of author's experience of applying KeyGraph to chance discovery in business. We analyzed the time-sequence of scores of ideas presented. Here, the originality and the reality of each idea were counted as the main factors for scoring, in order to reflect the social contribution. As a result, we are gaining reasons for introducing Innovation Game, with useful guidance such as to aim at several kinds of niche ideas reflecting player's situations. That is, the niche of activated ideas tends to be the source of novel, and useful, ideas (Tendency 1, 2, and 3). And, visualized connections between ideas help in creating ideas from combining familiar and novel clusters of ideas (Tendency 4). These findings partially correspond to previously presented hypotheses about the mechanism of innovation, but the experimental evidences showing the relevance between the activation of basic knowledge and the creation of ideas is new as far as we know. In the near future, we plan to count other factors for innovation such as user's demands and the use scenarios of created ideas.

ACKNOWLEDGEMENT

We appreciate Prof. Hirotada Ohashi, Prof. Kazuo Furuta, Prof. Kazuhiro Aoyama and colleagues in the Department of Systems Innovation in the School of Engineering, including colleagues in The Chance Discovery Laboratory, in The University of Tokyo, for supporting the evolution of innovation game. We express our thanks to colleagues in the Chance Discovery Consortium for enjoying the trials of our games. We also appreciate Prof. Hideyuki Horii, Prof. Yoichiro Matsumoto leading the Center for Knowledge Structuring, and the Faculty and research assistants of the Global COE members on Mechanical Systems Innovation for the in-depth discussions about the links between innovation and the structural visualization of knowledge .

REFERENCES

[1] Ohsawa, Y., and Usui, M.,Creative Marketing as Application of Chance Discovery, Ohsawa, Y., and Tsumoto, S. (eds) *Chance Discoveries in Real World Decision Making*, Springer Verlag, pp. 253-272 (2005)

[2] Ohsawa,Y , Benson, N.E. and Yachida,M, KeyGraph: Automatic Indexing by Co-occurrence Graph based on Building Construction Metaphor, *Proc. Advanced Digital Library Conference (IEEE ADL'98),* pp.12-18 (1998)

[3] Horie,K., and Ohsawa,Y., Product Designed on Scenario Maps Using Pictorial KeyGraph, *WSEAS Transaction on Information Science and Application*, Vol.3 No.7, pp.1324-1331 (2006)

[4] Berry, M.J.A. and Linhoff, G. (eds), *Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management,* John Wiley and Sons (2004)

[5] Ohsawa, Y., and Yada, K. (eds) : *Data Mining for Design and Marketing*, Francis and Taylor (2009)

[6] Ohsawa, Y., Data Crystallization: Chance Discovery Extended for Dealing with Unobservable Events, *New Mathematics and Natural Computation* Vol.1, No.3, pp.373 - 392 (2005)

[7] Maeno, Y., and Ohsawa, Y., Human-Computer Interactive Annealing for Discovering Invisible Dark Events, *IEEE Transaction on Industrial Electronics*, Vol. 54,No. 2, pp.1184 - 1192 (2007)

[8] Goldberg, D.E., *The Design of Innovation: Lessons from and for Competent Genetic Algorithms*, Kluwer Academic Publishers: Dordrecht (2002)

[9] Johansson, F., The Medici Effect: *Breakthrough Insights at the Intersection of Ideas, Concepts & Cultures*, Harvard Business School Press (2004)

[10] Gero, Against Ambiguity, *Computer Supported Cooperative Work* Vol 12, No.2, pp.153-183 (2003)

[11] Eris, O. *Effective Inquiry for Innovative Engineering Design*, Kluwer Academic Publishers: Boston, (2004)

[12] Gentner, D. (1988). Analogical Inference and Analogical Access, *Analogica*, 63-88, Pitman

[13] Dietrich, E., Markman, A.B., Stilwell, H., Winkley, M. (2003) The Prepared Mind: The Role of Representational Change in Chance Discovery, Ohsawa, Y., McBurney, P. (eds) *Chance Discovery* 208-230 (20039