知能と複雑系　132－32
(2003. 3. 15)

視覚的インタフェースからのチャンス発見における視点運動

大澤幸生

筑波大学ビジネス科学研究科 〒112-0012
E-mail: osawa@gssm.otsuka.tsukuba.ac.jp

あらまし　視覚的データマイニングにおいて、視覚化することの意義がいまだ明確な合意はない。しかし、チャンス発見の場合は、チャンス候補を注視点として提供しその周辺事象との関連を示すことが視覚化の目的にに他ならない。本論文では、チャンス発見指向の視覚的データマイニングツールのユーザに注視、周辺探索、再度中止という過程が起きることを実験的に紹介する。

キーワード　視点運動追跡、チャンス発見、視覚的データマイニング

Tracking Human Vision for Computer aided Chance Discovery

Yukio Ohsawa

† Japan Science and Technology Corporation, and

Graduate School of Business Sciences, The University of Tsukuba, Tokyo 112-0012 Japan

E-mail: osawa@gssm.otsuka.tsukuba.ac.jp

Abstract The eye-motions of the users of KeyGraph, a visual data-miner, is observed and analyzed. The shift of mental contexts, through new attention to significant events, have been regarded as the key to chance discovery Before such a shift, we found eyes' tendency of still glance at a certain point followed by saccade motions swinging with high frequency and amplitude, returning to the point of the still glance. This phenomena corresponds to a surprise at an event followed by the search for its relevance with surrounding events and reviewing of the discovered underlying meaning.

Keywords Vision tracking, chance discovery, visual data mining

1. Introduction

We must consider here that the choice of results from data mining is partially of the same kind of problem as the choice of events from the raw data. That is, the criteria for the choice depends much on the situation of the user, i.e., which pieces of information are the most significant for in the current situation of the user. In the domain of chance discovery, this is quite similar to asking for which events the human mind is prepared.

In the process of chance discovery, that one goes through the following process [Ohsawa02]: (1) Be concerned with chances suitable for the current situation (2) Understand the meaning of existing chances (3) Make decisions and actions on the chances and (4) Evaluate the chance and catch new concerns with chances.

I focus onto the mental state in the steps from (1) to (3) in this paper. Here, I show the phenomena observed in the motion of human eyes in catching the trigger of chance discovery from the output of a data-visualizer called KeyGraph [Ohsawa and Fukuda 02] and in the process of understanding the meaning of a chance just appeared.

2. The Process of Chance Discovery

The idealized process of chance discovery can be formalized using two parallel spirals, one of human perception and the other of data mining by a computer. The process starts from being concerned with chances in general, and goes to the understanding of the meaning of a certain chance. This was a hypotheses made on risk-management studies (a rare risk is a kind of chance) and on questionnaire analysis [Ohsawa and Nara 03]. However, these studies did not clarify how an individual human goes through these steps , nor how data mining tools for chance discovery make effects on the mind of user.

In this paper, we observe the eye motion of human looking for chances from the result of KeyGraph. The results coming out can be summarized that the user follows the steps below when they encounter new chances on the figure.

(1) Stare (have a still glance) at a certain point.

(2) Search relevant items to the point of (1) with fast and wide waving of eyes.

(3) Return to the point of (1).

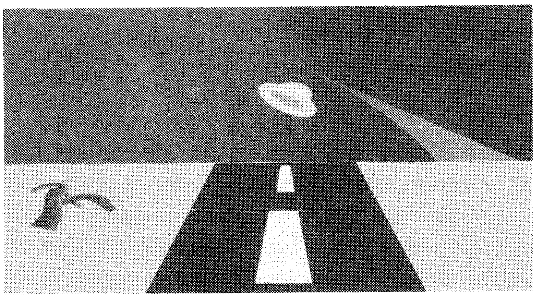

Figure 1. Just look...

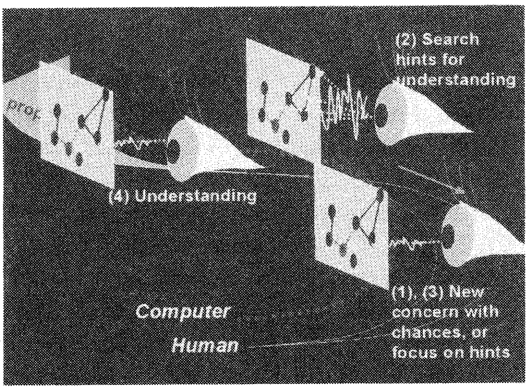

Figure 2. Eye motions in the process of chance discovery

The steps correspond to the acquisition of concern with a chance and its understanding.

3. Eye Motions with Chance Discovery

Let us quickly review reader's own eye-motions. When you meet a new event and be surprised, your eyes do not swing quickly. Suppose you are driving a car, and look at Figure 1. The flying object in the central front of your eyes may look like a space ship of extraterritorial intelligence, and your eye might have stopped at the object. However, soon you will notice the man running into your sight chasing the object, and you might have recognized the object as a hat blown off by wind from the man's head. In this step, you feel your eyes swing between the object and the man, quickly at first and return to the flying object.

If these things occurred to you, your experience here matches with our hypotheses. That is, our hypothesis is that we can observe the steps in the process of chance discovery as in Figure 1, as the corresponding phenomena of eye motions. Let me show the hypotheses, putting the expected eye motions and the corresponding steps of chance discovery pair-wisely as:

(1)[Chance discovery step 1]
Concern with the current chances:

Eye motion 1: Stopping high-frequency motions of eyes, i.e., focusing attention to a certain piece of information.

(2)[Chance discovery step 2] Unconscious search of the relevance between the focus and other pieces of information, i.e., search for the meaning of the chance.

Eye motion 2: High frequency (speed) swinging around an area surrounding the focal information, i.e., a saccade motion, [Arai 99].

(3)[Chance discovery step 3] Conviction of the meaning of the chance.

Eye motion 3: Stopping high-frequency motions of eyes. These hypotheses are summarized in Figure 3. In the remainder, let us show the real observation of eye motions of users of KeyGraph, that will be shown to support these hypotheses.

4. Experiment on Eye Motions with KeyGraph

As in [Ohsawa and Fukuda 02, Ohsawa and Nara 03], KeyGraph visualizes the complex structure of co-occurrence among events in data. Let a data be given as:

D = a1, b2, c1, d3, e4, ... z1.
a2, b1, (empty), d3, e4, ... z3.
a1, b2, (empty), d3, e4, ..., z1.
... (1)

Here "empty" means an item without a value given. For example, a questionnaire result data can be put in the form of Eq.(1) if we put the answer '1' for question with ID code of 'a' in the form of a *word* "a1" etc. and each answer-set of a subject as a *sentence* i.e., the sequence of items between two nearest periods ('.'s). A *document* as *D* in Eq.(1) is finally given, a set of sentences each including words in the sequence.

KeyGraph first takes the clusters of co-occurring (i.e., occurring in many same sentences) frequent items, calling each cluster an *island*. Items in islands are visualized in black (dense-black) nodes connected by solid lines as in Fig. 3. Then it extracts items to be the candidates of chances, which may not be so frequent as those in islands but bridge between the islands. These items are chosen if their co-occurrence with ones in multiple clusters are strong. The bridging items are visualized by red (light-colored in B/W figure) nodes connected to islands via dotted red lines.

All in all, the chance-candidate nodes and the dotted links show comparably rare but essential parts of KeyGraph from the aspect of the structure of items in the data. In this sense, red nodes has a high possibility to mean what we mean "chance" above. We have a number of cases where these significant rare items made hints for users in discovering new opportunities or risks, which are uncertain but is very essential for decision making [Ohsawa 02, Usui 03].

In the following experiments, we applied a set of KeyGraphs for questionnaire results: Each item in D means the answer to one question or a word in a free-sentence answer, and each sentence corresponds to the answer-set of an interviewee.

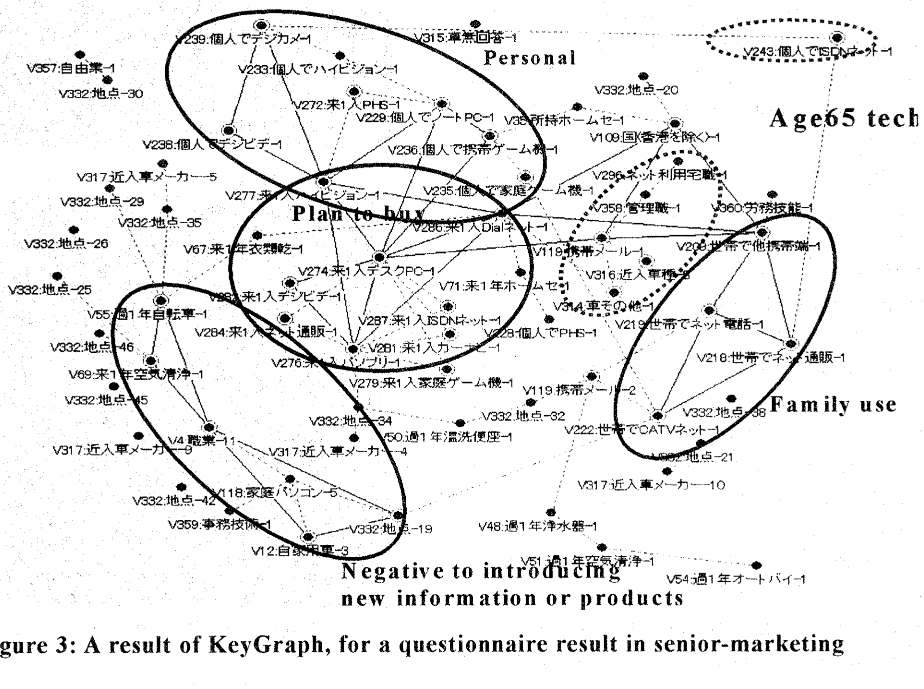

Figure 3: A result of KeyGraph, for a questionnaire result in senior-marketing

In Figure 3, let me show the example of KeyGraph for one of the questionnaire data we used in the eye-motion experiment. First you should look at the figure to see what the whole things are like. You find two islands, one meaning senior people preferring to keep classical life with instruments as bicycles, refrigerators, etc., and the other meaning ones frequently using IT tools. Based on these understandings, you can find the nodes and (dotted) links between clusters show events to occur at stages of the shifts between islands. Also you can find the left-end and the right-end are connected via a shot-cut bridge meaning new purchases of IT tools with leading technologies.

If you see the graph in this way, you experienced a typical macroscopic pattern for the movement of view-focus. This sketch of typical eye-motions answers the meta-level (abstract) question "how do users look at KeyGraph?" or, more generally "how do users look at visualized data?" if the user uses a visualizer based on a similar concept as KeyGraph, say co-occurrence based 2D arrangement of node as in [Sumi and Mase 02] that has been designed for aiding user grasp the relations among concepts. On the other hands, a microscopic pattern of eye movement helps in answering your question if you ask "what part of the output should I look for discovering significant chances?"

If you only have the macroscopic knowledge about eye-motions over KeyGraph, you cannot tell which of the two bridges between the two islands is more significant in Fig.3 for example, because user normally looks at both while looking at all over the figure. However, if you see some subtle difference in the user between the times of looking at one bridge and the other bridge, then you may understand what information in the figure triggered the impressive discovery for the user. In other words, we can identify chances for users on microscopic eye motions.

The experiment we made was on the system of FreeView HMS (product of Takei Instruments Co. Ltd.) applied here as the head-mount sensor with data processor. The data of eye motions is obtained as in the form of (angle-X, angle-Y, and values of other attributes) for each moment of sample moment, where angle-X and angle-Y denotes the angle of the center of the view focus from the front direction of the glass.

The data, if we see the time sequence of angle-X and angle-Y, can be visualized in a simple visualizer as in Figure 4 and 5 respectively. Then, on the hypotheses in Section 3, we can pick the moments at which the user might have been hinted by the information acquired from his./her vision focus in the figure. That is, a time when the high-frequency swinging in eye-motions decreased in amplitude can be regarded as these hinting moments according to conditions (1) and (2) in Section 3. I did this selection of moments in all the cases taken from the system, as exemplified in the circular nodes in Figure 4 and 5.

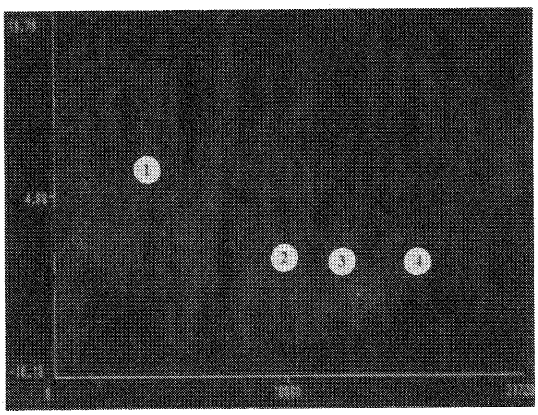

Figure 4. The time series of Angle-X

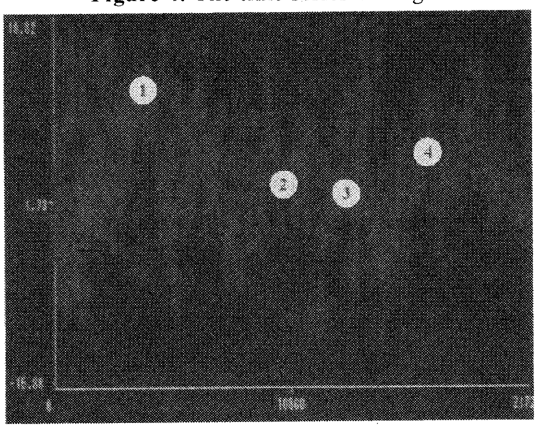

Figure 5. The time series of Angle-Y

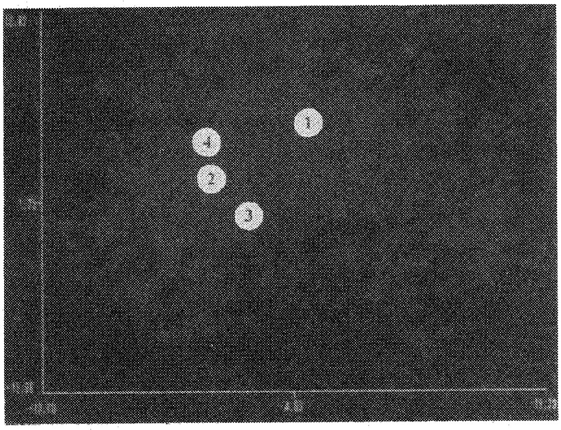

Figure 6. X-Y distribution of view-centers, and their positions at hinting moments

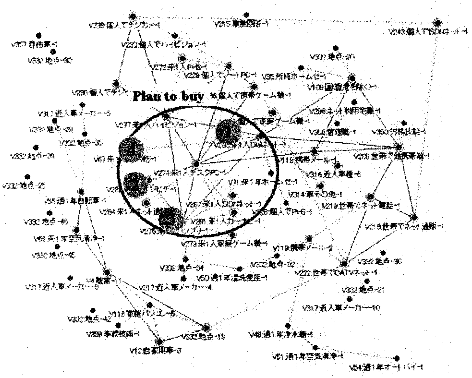

Figure 7. The hinting view-centers, located in the KeyGraph.

Here, for strictness we should take the time-window near each moment and apply Fourier transformation, but I tentatively took the moments where changes corresponding to (1) and (2) in Section 3 occurred as apparently as to seen just by looking at the visualized results as Figure 4 and 5. This is because the size of time-window is hard to be fixed for the time being because of the complexity of eye motion, and I am currently making a Wavelet transformation tool for this specific purpose.

The four candidates of hinting points are reflected to Figure 6 and 7, where the points corresponding to the candidates are located in the 2D interface. From Figure 7, we find a significant concentration of the candidate hints to the central circle of Figure 7, corresponding to the questionnaire answers about subjects' desire to buy new IT tools in a near future. Especially, after the moment of node 2, i.e., when the first hint in the bound between the two islands in Figure 3 was acquired, the user's focus came to be the most concentrated into the central circle. It is also noteworthy that a friend of the subject user came across in the experimental environment to talk to the user near the moment of node 4, where sudden peaks of eye-motions interrupts. Even in this perturbing situation, the eyes of the user returned to the cluster of answers about IT tools.

Another noteworthy point in Figure 4 and 5 is that the moment of node 4 rather embarrassed the user, and this is a switch from (1) to (2) in Section 3, not followed by a confirmed understanding (4). After taking off the head mount sensor, this user really said he did not understand what the node of 4 in Figure 7 meant although he remembered he payed attention to the corresponding area for a while. He also reported that his interest was in the center and the answers abour IT tools.

Having heard the four points might have aided his understanding, he said the points 2 and 3 really did so but 1 did not contribute so much and 4 did even less. From Figure 7 and 8, we see that the points seen at moments 1 and 4 were not reviewed, i.e., these pointes were not looked at again after the eyes passed over them. That is, our hypotheses in step (4) of Section 3 came to be supported in this example, i.e., a low-frequency "looking around" phase means the understanding and the high-frequency saccade motions meat the search of hinting pieces of information.

We took 3 cases of KeyGraph for the data of questionnaire, each case given by the pair (subject, target figure). In these cases, 13 candidates of hints were taken in the similar manner as above, 5 of which also satisfied the condition of hypothesis of (4) in Section 3. In the interview after each subject looked at the figure in the system of Figure 6, 3 of the 5 nodes (answers) they chose corresponded to the 5 most probable hints above. Because we had 30 to 70 nodes in each figure, 130 nodes in total for all target figures and they selected only 5 points in figures in total for Q1.

5. Conclusions

Eye-motions were observed for validating the process model of chance discovery, starting from the concerned attention with chances and reaching the understanding of chances via the search of relevance-links around chance-events. The hypotheses were supported by the experiments.

In the future work, we plan to make further experiments to refine validate the hypotheses.

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