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ORIGINAL PAPER

Eye-tracking based adaptive user interface: implicit human-computer interaction for preference indication

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Abstract In this paper, we proposed and evaluated an adaptive recommendation system based on users' eye-tracking data and an optimization algorithm called IGA. An eye tracker was utilized to acquire users' eye movement data and extract three measures, which were respectively number of fixation, fixation duration and the first fixation on target item. Based on the results on the three measures, we inferred users' preferences and adjusted the user interfaces based on users' preferences. We developed a prototype system, which could adaptively recommend digital cameras to users. Then we conducted a user study with the prototype system and found that participants could identify their preferred products with a comparatively less time period and higher satisfaction.

Keywords Eye-tracking · Adaptive user interface · Preference inference · Human-computer interaction

1 Introduction

Many computing systems or services start to make use of intelligent mechanisms to increase adaption of user interface [11]. For instance, Amazon.com collects user behaviors within the online service and recommends other related books based on the inferred user preferences so as to reach its commercial goals. There are two key challenges with such a recommendation system: first, the system should be able to infer users' preferences accurately enough; second, data collections of user behaviors for further inference of user preferences should be natural and easy enough for both end users and the system itself. There are commonly two types of methods to collect users' feedbacks for further preference inferences [4]:

The explicit methods often require users' additional operations. For example, users can rate recommended books by manually clicking buttons indicating their preferences e.g. "I hate it" to "I love it" in Amazon.com, and the system would evaluate the users' preferences based on a collection of such user feedbacks and recommend other book products. The explicit methods, like the manual rating systems, require extra operations from users while they are using a system, and are not optimal ways of collecting user feedbacks.

The implicit methods often record and interpret natural user behaviors during their interactions with systems, for example, mouse movements and clicks, scrolling and elapsed time [3]. For example, Amazon.com also records the books clicked by users, and recommends similar books to end users. The implicit methods automatically collect identified user data and analyze them requiring no extra operations from users. But a challenge with the implicit methods is that it needs to ensure accurate inference or reasoning based on the automatically collected user data. The challenge is often due to that there is no one to one mapping between user behaviors and their preferences on the semantic level. For example, sometimes when a user clicks one book in Amazon.com, it does not always mean s/he likes it; instead, s/he may click it by mistake.

Compared to explicit methods, the obvious advantages of implicit methods are that they require no extra operations

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from users and user data collected via those methods are more reliable since they are real data of user behaviors. If the inference or reasoning based on such user data reaches satisfactory level of accuracy, the implicit methods will be more useful designing adaptive user interface.

Eye movement data including e.g. position and duration of eye gazes were potentially good measures for implicit methods because user attention was often associated with both spatial and temporal characteristics of eye gazes according to many previous works [15]. Some systems, for example, gaze driven speech synthesized system [15] and our previous product recommendation prototype system [2], made use of eye-tracker to record data of users' eye-movements when the users browsed contents displayed on screens. They analyzed the eye-tracking data to explore users' attention allocations on displayed objects, subjective preferences on different contents, cognitive processing depth for different visual information, and even to detect user emotions. Based on such analysis, systems can then provide adaptive interfaces to users. Compared with other measures of user behaviors e.g. mouse clicks, eye-tracking data are often viewed as a more direct way of understanding user attentions [1]. Moreover, the eye-tracking based systems enable heavily-disabled people to interact with computers. Studies on what measures from eye-gaze data are good indicators for user intentions or preferences would enhance the interaction efficiency for such user groups. However, there are also some disadvantages for collecting eye-tracking data: first, users need to wear accessories to enable collection of eye tracking data. With the development of the eye-tracking technologies, this becomes a less important issue and there are many eye-trackers supporting data collection while people are moving. Second, data of eye gazes are not always highly associated with user attention and there are a lot of noises as well [7]. Good indicators need to be explored and elicited from a huge amount of eye gaze data via proper studies.

In this paper, we proposed a product recommendation system based on a pre-analysis of users' eye tracking data when they view images of such products. The main works of this paper is based on our previous research [2], and include three parts: we first analyzed users' eye movement data and identified the key preference measures; then we set up a framework for an adaptive user interface based on the eye-tracking measures and an interactive gene algorithm (IGA); and finally, we developed a prototype that can recommend camera products and conducted a user study with it. In the rest of the paper, we firstly review some related works and compare our method with them. Then we present the framework for the adaptive user interface, the identified eye-movement measures, and the application of IGA. We develop a prototype system that can recommend camera products based on users' eye tracking data. Finally, we conduct a user study to evaluate the system.

2 Related works

In the session, we review relevant works and discuss their differences from our works. Qvarfordt and Zhai [13] found that when people were interested in an object displayed on a screen, they tended to look at it with higher gaze intensity and longer accumulated duration. Based on this principle, computer systems could provide information adaptively based on users' visual interests. There were some well established systems provided adaptive user interfaces by making use of eye-tracking data. The adaptations covered both contents and layout changes. For example, an adaptive E-learning system provided users optimized learning materials based on user preferences that were inferred from eye movement data of users [5]. The system was integrated with a real time eye-tracker and could hide pictures automatically if users preferred texts. It could also display additional contextual information (e.g., texts, other picture, or videos) for the attended pictures of users. Xu et al. [17] proposed a recommendation algorithm for information retrieval. They asked users to look through images that were provided by search engines. During the process, they recorded people's eye movements with an eye tracker. Based on an analysis of the eye movement data, the system would update the image list and the most attended images by users would be moved to the top of the list. In the sense, users could find the most desirable or interested images easier.

But as we mentioned in previous sessions of this paper, such systems supporting adaptive user interfaces based on eye movement data may cause some problems due to noises in the eye tracking data. A common problem is the "Midas Touch" [9]. Many times users would pay unconscious visual attention to displayed objects that are with attractive colors or unusual shapes. Eye trackers would record such "noise" data and systems can hardly differentiate them from the conscious visual attention objects. Such noise data would result in wrong adaptations of user interfaces and decrease usability of such systems.

To avoid adaptation mistakes mentioned in the previous paragraph and improve the accuracy, we could resort to mathematical optimization methods. We can view the adaptation to users' preferences as an optimization problem in mathematics: systems search databases and design spaces, and push related contents and UI components to users via the adaptive UI. For an optimization process making use of eye movement data, a system evaluates all possible solutions through users' eye-movement data, and adjusts the search strategy to generate a more reliable proposal.

Interactive gene algorithm (IGA), as an optimization method in mathematics, is a suitable method to be applied in adaptive systems that makes use of eye-tracking data. It is a good optimization method that can be applied in e.g. engineering fields, where optimizations often have clear and structural objectives. Such structural objectives can be described with explicit functions. Based on the well-defined functions for optimization objectives, applying IGA can help to search proper solutions automatically without involving users' subjective feedbacks. However, to formulate structural functions to describe people's preference on e.g. arts, design or other similar field is difficult. Hence, if we want to accurately describe users' preference, we need to get subjective feedbacks from users to tune the optimization strategies. In our proposed system, IGA and feedbacks from eye movement data were combined to optimize the inference on user preferences. Recently, there are researchers considering integrating eye-movement data as subjective feedbacks for IGA based applications. The approach could decrease users' fatigue in assessment and provide feedbacks to the interactive evolutionary application. For instance, Pallez [12] proposed an eye-tracking based IGA application to calculate fitness for solving the OneMax Problem [14].

With this paper, there are two main research challenges:

(1) There has never been a proposed approach to provide an adaptive user interface by integrating both eye-movement data and IGA;
(2) Moreover, there are few studies exploring how to model users' preference based on eye-movement data especially in product recommendation domain.

3 Preference indicators in eye movement data

3.1 Introduction of eye-movements data

There are basically four categories of movement data for human eyes: saccade, fixation, smooth pursuit and nystagmus [8]. Fixation is the most often used measure among the four types of data in human-computer interaction studies because eye fixations on an object often associate with information perception and processing of the focused object [7]. Generally, an eye fixation is a relatively stable eye-in-head position within some threshold of dispersion (typically $< 2°$) over some minimum duration (typically 100–200 ms), and with a velocity below some threshold (typically 15–100°/s) [7]. In practice, there are some extended measures from eye fixations, such as number of fixations, fixation duration, and accumulated fixation duration on Area of Interest (AOI) [13].

How to map these measures with relevant visual perception and processing processes is a key challenge in analysis and explanation of eye movement data. There are currently two methods to calculate and explain eye movement data: the "top-down" and the "bottom-up" approaches [7]. With the top-down approach, researchers consider subjective motivation or intention of users as the primary driving factor for eye movements. Yarbus [18] found that people look at different parts of a painting with different motivations and tasks. Koivunen et al. [10] asked users to conduct different tasks with the same product designs. The tasks were either assessing first impression, evaluating usability or commenting aesthetics. They concluded that people looked at the same product in different ways depending on their tasks. With the bottom up approach, researchers consider visual stimuli as the primary driving factor for eye movements. In our proposed system, we consider both user motivation or intentions and the presented images for cameras as we assume that both of them would affect our choices of eye movement measures for the inference of user preference.

3.2 Experiments

In our previous work, we selected some eye movement data as measure without support from experiments [2]. Hence, in this paper we designed an experiment to explore proper measures out of eye movement data in the context of product recommendation. We asked participants to search their preferred digital cameras only by browsing their images displayed on a computer display. A task would be complete, when a user orally reported the camera that s/he preferred. Users' eye movement data were recorded with the ASL™ eye-tracker. Every image for digital cameras could be viewed as an AOI, and there were either four or six different images displayed in the computer screen during the experiment and they were denoted as AOI_1 to AOI_4 or AOI_6 (see Fig. 1).

As shown in Fig. 1, we asked each participant to tell us which camera was the preferred one, and then we analyzed users' eye movement data during the task. Taking Fig. 1(c) as an example, we found that AOI_1 had the most number of fixations among all AOIs for a participant, which was also the preferred camera according to his oral report.

Nine participants (denoted as P_1 to P_9 in following tables and figures) took part in the experiment. And due to limit on paper pages, we only show part of experiment results in detail. In the next three sessions, we present the experiment results on respectively three measures: number of fixations on AOI; duration of fixations on AOI; and first fixation on AOI. When we present the results, we highlighted them against user preferences that were orally reported by all participants.

(1) The number of fixations on each AOI (Table 1).

Based on the fixation number results, we categorized the cameras into two groups: the preferred and not preferred. Preferred group includes preferred product images orally reported by participants, and not preferred group includes the rest ones. Figure 2 shows the results from each participant.

According to Fig. 2, users gazed at the images of the preferred cameras with more fixations, which indicate that the

(a) different colors and same structures

(b) same colors and different structures

(c) different colors and different structures

Fig. 1 Examples of saccade path and fixations on each AOI for different experiment materials

Table 1 Number of fixations on each AOI, and the items labeled with * are the preferred ones orally reported by all participants

	AOI_1	AOI_2	AOI_3	AOI_4	AOI_5	AOI_6
P_1	13*	6	3	2	1	0
P_2	0	2	0	1	6*	0
P_3	1	5	7	3	16*	10
P_4	2	2	2	6*	0	1
P_5	4*	1	1	3	1	1
P_6	1	1	0	1*	0	0
P_7	0	1	0	1	1	6*
P_8	5*	1	2	5	8	1
P_9	1	1*	1	1	0	1

number of fixations can indicate users' preference, and the more fixations on an image, the more preferred the corresponding camera by users.

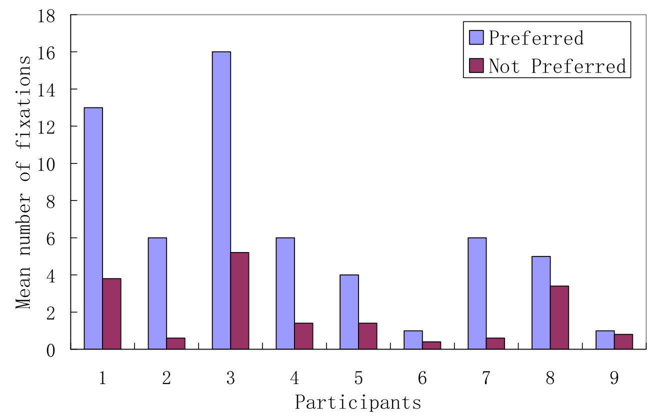

Fig. 2 Mean numbers of fixations on preferred and not preferred cameras for each participant

Table 2 Duration of fixations on each AOI, and the items labeled with * are the preferred ones orally reported by participants

	AOI_1	AOI_2	AOI_3	AOI_4	AOI_5	AOI_6
P_1	3.55*	2.27	0.64	0.67	0.17	0
P_2	0	0.14	0	0.3	1.24*	0
P_3	0.09	0.75	0.83	0.34	2.53*	1.29
P_4	0.41	0.47	0.47	2.54*	0	0.43
P_5	1.67*	0.22	0.38	0.62	0.35	0.2
P_6	0.27	0.21	0	0.47*	0	0
P_7	0	0.43	0	0.41	0.52	1.34*
P_8	1.67*	0.23	0.28	0.59	1.35	0.31
P_9	0.06	0.06*	0.06	0.07	0	0.11

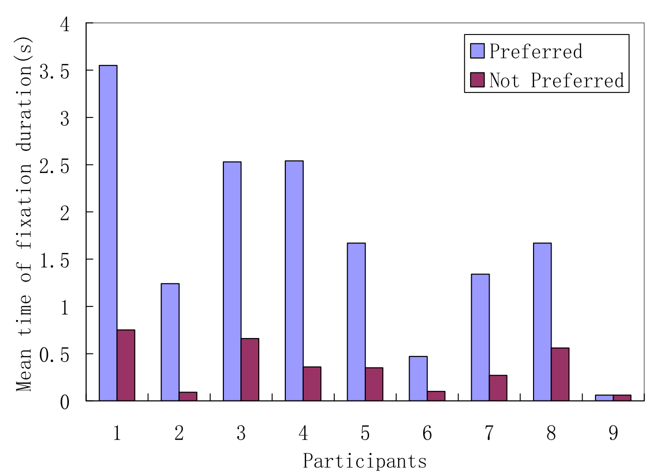

Fig. 3 Duration of fixations on the preferred and not preferred AOIs of each participant

(2) Duration of fixations on each AOI in second (Table 2).

Figure 3 shows the mean duration of fixations on the preferred and not preferred AOIs.

Table 3 Each participant's first fixation on AOI

	AOI_1	AOI_2	AOI_3	AOI_4	AOI_5	AOI_6
P_1	+*					
P_2				+	*	
P_3				+	*	
P_4			+	*		
P_5	*			+		
P_6	+			*		
P_7						+*
P_8	*		+			
P_9	+	*				

"+" indicates the AOI where the first fixation located
"*" is the preferred camera a participant had chosen

From Fig. 3, we can see that users gazed at the preferred AOI for longer durations. In the sense, the fixation durations can also indicate users' preferences, and the longer fixation durations on an image, the more preferred the corresponding camera by participants.

(3) The first fixation(s) on the target AOI.

As mentioned in the previous paragraphs, the number of fixations and the duration of fixations can be the measures for inferring user preference based on the "top-down" approach. Besides, we explore other eye movement measure based on the "bottom-up" approach in the experiment, for example, the first fixation(s) on the target AOI. These fixations draw user's visual attentions within the first 200 milliseconds by an individual AOI [16]. It is a useful measure when a specific visual search target exists [7], and can tell us the first impressions on the visual elements. We recorded each participant's first fixation on AOI in the experiments, and the results are shown in Table 3.

According to Table 3, we note that sometimes the first fixation(s) on one AOI does not indicate the users' preference, and it is only involuntary reflection. However, it often indicates that the AOI includes visual objects with abnormal colors or shapes. Hence, when we utilize the first fixation as a measure to infer users' preference, we should take its both advantages and disadvantages into account.

4 Adaptive user interface based on eye-tracking and IGA

We build our adaptive system based on eye-tracking data and IGA with a few modules, and the framework is shown in Fig. 4.

We describe the main modules of the framework as follows:

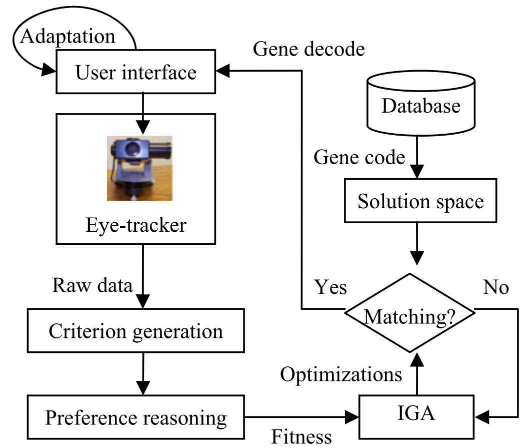

Fig. 4 The framework for our adaptive system based on eye-tracking and IGA

Preference inference The raw eye movement data is acquired by an eye tracker, and analyzed on the three measure criterions mentioned in the previous session of the paper: the number of fixations, the duration of fixations, and the first fixation on target AOI. Then to interpret the measures for preference reasoning, we construct the function P_i:

$$P_i = a_{nf} m_{nf} + a_{tf} m_{tf} + a_{ff} m_{ff}$$

Here, P_i represents the degree of preference for the AOI_i, and how m_{nf}, m_{tf} and m_{ff} are calculated are shown as below:

$$m_{nf} = \frac{\textit{number of fixation on } AOI_i}{\sum \textit{number of fixation on } AOI_i}$$

$$m_{tf} = \frac{\textit{time of fixation duration on } AOI_i}{\sum \textit{time of fixation duration on } AOI_i}$$

$$m_{ff} = \begin{cases} 1, & \text{first fixation on target } \mathrm{AOI}_i \\ 0, & \text{first fixation not on target } \mathrm{AOI}_i \end{cases}$$

and a_{nf}, a_{tf}, a_{ff} are the weights for the measures of m_{nf}, m_{tf}, m_{ff} respectively. We can value a_{nf}, a_{tf}, a_{ff} via empirical studies, and adjust them with their different contributions for the preference indication.

IGA IGA was developed based on Genetic Algorithm (GA). It was inspired by natural evolution mechanisms such as crossover, mutation, and survival of the fittest individuals. IGA enable 'interaction' with real usages and users' subjective responses (such as emotion or preference) as fitness value when the fitness function (to assess the performance of an individual) can't be formalized effectively [6]. The general process of IGA is shown as follows [6]:

Step1. Initialize the population (solution space) of chromosomes.

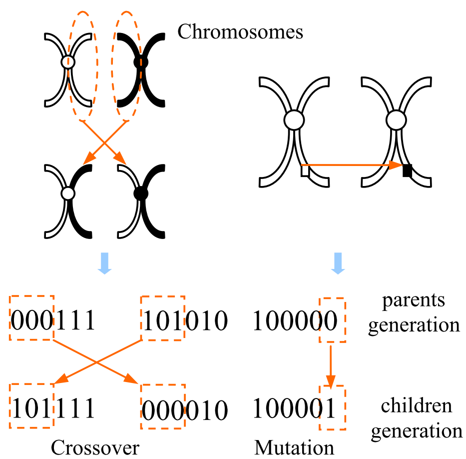

Fig. 5 Examples of crossover and mutation operations in IGA

Step2. Calculate the fitness for each individual using fitness function based on user's subjective feedbacks.

Step3. Reproduce individuals to form a new population according to each individual's fitness.

Step4. Perform crossovers and mutations on the population.

Step5. Go to ***Step2*** until some predefined conditions are satisfied.

Chromosomes are usually encoded by bit strings, and each bit like one gene. Crossover operation swaps parts of strings of parents' generation to children generation. Mutation operation inverts some bits of parents' generation to children generation. Reproduction operation copies the bit strings themselves (usually have the highest fitness value) to children generation. The crossover and mutation operations are shown in Fig. 5.

During the evolution process, these operations can be viewed as operators in the algorithm. The operations are also restricted by the probability to prevent being limited to get local optimum solutions or generating too huge solution spaces to get the optimum solutions quickly. In our work, the crossover probability is 0.8, and the mutation probability is 0.005.

We calculate the fitness F_i for each AOI$_i$ with P_i from the preference reasoning module:

$$F_i = P_i R(t)$$

In the above equation, $R(t)$ is the function for the degree of confidence, which ensures the fitness's accuracy. Our previous work [2] ignored users' learning process, but in practice, users usually need a period of time to get familiar with the eye-tracking based interaction. At the beginning, users usually don't pay much visual attention to the AOI which is their final preferred choice. So the accuracy of preference reasoning will be low at early period, but it increases along the continuance of interaction process. $R(t)$ is defined as follows:

$$R(t) = \begin{cases} 1 - e^{-t} & (t < T_s) \\ 1 & (T_s \le t \le T_f) \\ e^{T_f - t} & (T_f < t) \end{cases}$$

T_s is the thread of time to describe how long the user will be familiar with the interaction. $R(t)$ increases along the t increases, and its maximum value is 1. It means the user has already got familiar with the eye-tracking based interactions. The eye-movements data based preference reasoning has the highest confidence. T_f is the thread of time to describe how much users get tired when they use the system for a long period of time. The preference inference accuracy would also decrease. Usually, T_s and T_f need to be defined empirically.

Adaption We set up a database to store the user interface design solutions, including layout styles, images, and text information, etc. Then we code them into bit stings, and all strings generate solution spaces where IGA can search for the optimum solutions. If the optimum results don't match any of solutions in the solution space, the IGA will restart its calculation in a new turn; otherwise, the solution will be decode, update the user interface.

5 Prototype system

5.1 Product recommendation prototype

We treat product recommendation as an optimization problem: system searches the solution space (product database) and pushes possible solutions (user's preferred product) to users; during the process, the system updates the search strategy by integrating the inferred users' preferences based on eye movement data. The recommendation system interprets the strings of products information from the database by IGA, and the user interface updates the information adaptively.

Digital cameras (DC) are the main products covered in the prototype system and their industrial design information, including brands, colors, and visual structures are presented with product images. And to apply IGA for product recommendations, we model the product information in the database with binary coding as follows:

- Brand: Canon-000, Sony-001, Nikon-010, Samsung-011, Panasonic-100, Fujifilm-101, Olympus-110, KODAK-111;
- Colors: white-000, black-001, red-010, blue-011, gray-100, pink-101;
- Structure: single lens reflex-1, else-0.

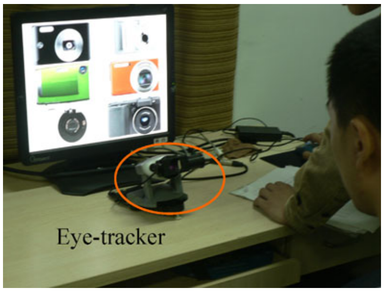

Fig. 6 Prototype system for product recommendations

Fig. 7 Participants calibrate the eye tracker

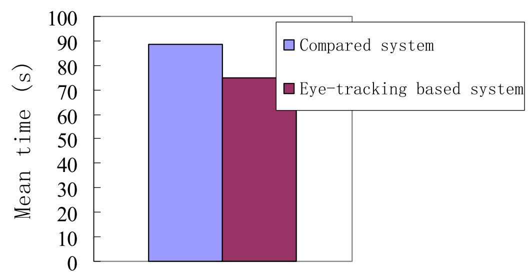

Fig. 8 Mean time participants used with the two systems

Hence, each DC in our product database can be viewed as one chromosome which has several genes like blow:

$C = 0010011$

We had chosen total 220 different DCs and their information from the Internet to set up the product database.

We composed and applied a C++ program to read raw eye movement data from ASL^{TM} Eye-tracker SDK. In the system, the display has been divided into 6 AOI (see Fig. 6).

To avoid the effects from positions on the eye-movement data (e.g., some users usually gazed AOI_1 at top left firstly), the system locate DCs randomly on different AOI with each generated UI. And in order to balance the influence of persistence of vision out (participants' visual attention were often influenced by visual objects in the previous user interface), there was one display with a black dot on white ground for several seconds between any two adjacent generation UIs. This inserted irrelevant display could reset participants' visual attention for each new generation UI.

5.2 User study

We conducted a user study to evaluate the prototype system. Altogether nine participants aged from 20 to 28 took part in the user study. Four of them have their own DCs already, the others planning to buy one. We ran the study with two personal computers with 1.7 GHz Pentium 4 processors and 1G of RAM, with one supporting participant's interactions and the other assisting eye-tracker operations. Each PC had a LCD display with a 1024×768 resolution. A RS H6 eye-tracker developed by ASL^{TM} was applied in the system, whose sampling frequency was 60 Hz and its accuracy was 0.5 degree. It had an analysis module and could extract a fixation as described blow: it started when 6 consecutive samples fell within 0.5 degree and ended when 3 consecutive samples fell outside of 1 degree; all samples within 1.5 degrees were included to calculate the fixation location.

At the beginning, participants were asked to simply view some pictures with e.g., nine points for eye-tracker calibrations (see Fig. 7). Then we adjusted their sitting-height and distance form the display so that the eye-tracker could record their eye movement data successfully.

Then participants were presented DC images that were generated by IGA. In the first presentation, system chose DCs randomly from the database, and then made adjustments based on user preferences inferred from eye movement data later on. Participants were asked to browse the screen to search the most preferred DC without reporting them. In the experiment, whenever they want to they can press any key in the keyboard to change to the next generation UI for new recommendation. This task would end until each participant found two preferred DC that they wanted to buy, or they found none preferred when the IGA evolution generation exceeded 25.

Participants were divided into two groups randomly, with one group five participants, and the other four. Two groups of users were asked to use our system and another compared system, with one group using our system first and the other group using the compared system first. The compared system had no eye-tracker or IGA applications, participants can only browse images of DCs by clicking "next page" or "previous page" buttons to search the preferred ones. Each participant was asked to tell the search results after the experiments, and fill in a questionnaire for subjective preferences.

The results of user study are presented as follows:

Task duration The task completion time of each participant was recorded. Figure 8 shows the mean duration for all

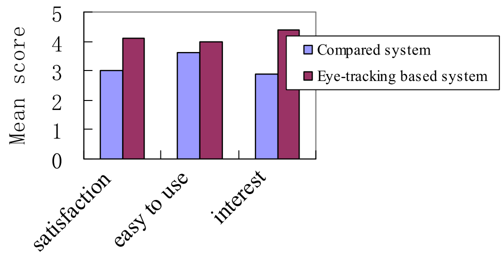

Fig. 9 Subjective scores for two systems

participants. It was found that participants spent comparatively less time with our eye-tracking based system.

Accuracy In order to check the accuracy of our eye-tracking based recommendation system, we calculated the DC with the maximal fitness values for each page of recommendations. And after the experiment, we asked participants to report their preferred DCs. And we found that about 90% of the DCs with the maximal fitness values were the preferred ones by end users.

Subjective experience We applied a 5-point Likert scale to measure subjective experiences of participants with both systems on three measures: overall satisfaction (1—very dissatisfied, 5—very satisfied), level of easy to use (1—very difficult to use, 5—very easy to use), and degree of interest (1—not interested at all, 5—very interested). The mean scores for both systems are shown in Fig. 9. Generally, participants gave higher average scores to our eye-tracking based system.

6 Conclusions and future work

Motivated by natural human-computer interactions and evolutional computing, we employed eye movement data to infer user preferences with IGA. Then we presented an adaptive recommendation system to end users based on the inferred user preferences. We developed an adaptive product recommendation prototype, and a user study of it also showed that it could improve the efficiency and satisfaction for seeking product information.

Our future work will focus on improving the eye-tracking based users' preference inference and especially the optimizations of eye movement data measures to enhance inference accuracy and efficiency. We also plan to design eye-tracking based adaptive user interface with similar mechanisms, not only for desktop systems, but also in the field of pervasive computing systems.

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