Hyperinteractive Evolutionary Computation

Benjamin James Bush and Hiroki Sayama, *Member, IEEE*

***Abstract*—We propose hyperinteractive evolutionary computation (HIEC), a class of IEC in which the user actively chooses when and how each evolutionary operator is applied. To evaluate the benefits of HIEC, we conducted three human-subject experiments. The first two experiments showed that HIEC is associated with a more positive user experience and produced higher quality designs. The third experiment demonstrates the potential of HIEC as a research tool with which one can record the evolutionary actions taken by human users. Implications, limitations, and future directions of research are discussed.**

***Index Terms*—Collaborative work, computer interface, human factors, interactive computing, interactive evolutionary computation.**

I. Introduction

EVOLUTIONARY computation has been successfully used to optimize a large class of ill-behaved or otherwise intractable objective functions. The majority of these evolutionary methods require an explicit or algorithmic description of a fitness function with which to evaluate the quality of potential solutions (henceforth referred to as "individuals"). However, there are many fitness functions, such as those which involve aesthetics, for which no such explicit or algorithmic description is easily obtained.

Interactive evolutionary computation (IEC) is a derivative class of evolutionary computation which incorporates interaction with human users. A comprehensive review of IEC theory and application was given by Takagi [1]. Most IEC applications fall into a category known as "narrowly defined IEC" (NIEC) [1]. In NIEC, the task of fitness evaluation is outsourced to human users. For example, a user may be presented with a visual representation of the current generation of individuals. The user is then prompted to provide fitness information about some or all of the individuals. The computer in turn uses this fitness information to produce the next generation of individuals through the application of a predefined sequence of evolutionary operators [1], as illustrated in Fig. 1.

As a design tool, NIEC has some disadvantages. One set of disadvantage stems from the confinement of the user to the role of selection operator. Creative users who are accustomed to a more highly involved design process may find the experience to be tedious, artificial, and frustrating. This issue has been addressed in previous work. For example, Bentley and O'Reilly [2] stressed the importance of instilling in the user a strong sense of control over the entire evolutionary process. Similarly, Shneiderman and Plaisant [3] required that system users be the initiators of actions rather than simply responding to prompts from the system. These principles apply generally to any human-computer interactive system, but have not been fully considered in the design of current IEC frameworks.

These lines of research suggest that enhancing the level of interaction and control of IEC may be beneficial. Therefore, here we propose hyperinteractive evolutionary computation (HIEC), a novel form of IEC in which a human user actively chooses when and how to apply each of the available evolutionary operators, playing the central role in the control flow of evolutionary search processes (Fig. 2).

We expected that evolutionary design with HIEC would produce a more controllable and positive user experience, and thereby better design outcomes, than those with NIEC, but potentially with increased user fatigue due to the more complex interface. To examine these issues experimentally, we developed two software applications for designing colorful, animated patterns using kinetically interacting self-propelled particles. The first application was based on NIEC, while the second one was developed by converting the first one into an HIEC-based application. Using these two applications, we conducted three human-subject experiments.

In the first experiment, individual subjects used the NIEC and HIEC applications to evolve aesthetically pleasing patterns. We quantified, using questionnaire, user experience outcomes such as ease of operation, controllability, fun, overall satisfaction, and user fatigue, in order to quantify potential differences in user experience between the two applications. In the second experiment, subjects formed groups and worked on the same task as that of the first experiment, but the qualities of final designs produced were assessed collectively by group evaluation. The purpose of this experiment was to compare the quality of the designs generated with HIEC with those generated with NIEC. In the third experiment, we modified the HIEC application to keep a complete log of the evolutionary events taking place within an HIEC run. Subject groups were then instructed to use the HIEC application under different conditions. This experiment was to explore the potential of HIEC as a research tool for studying user behavior.

The rest of this paper is structured as follows. In Section II, we propose the basic architecture of HIEC and discuss its relationships with other IEC technologies. Section III provides details of the two software applications we developed, followed by detailed descriptions of the three experiments we conducted. Discussions, including limitations and future research directions are given in Section IV.

Manuscript received May 18, 2010; revised September 3, 2010; accepted November 12, 2010. Date of publication January 28, 2011; date of current version June 24, 2011. This work was supported in part by the National Science Foundation, under Grants SES-0826711 and DUE-0737313.

The authors are with Binghamton University, State University of New York, Binghamton, NY 13902 USA (e-mail: benjaminjamesbush@gmail.com; sayama@binghamton.edu).

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Digital Object Identifier 10.1109/TEVC.2010.2096539

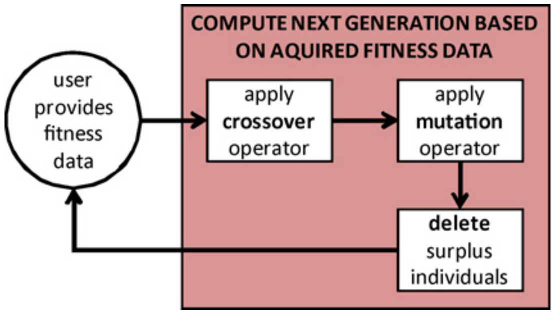

Fig. 1. Control flow of a narrowly defined IEC (NIEC) application. The user is prompted for fitness information once each generation but has no control over the overall search dynamics.

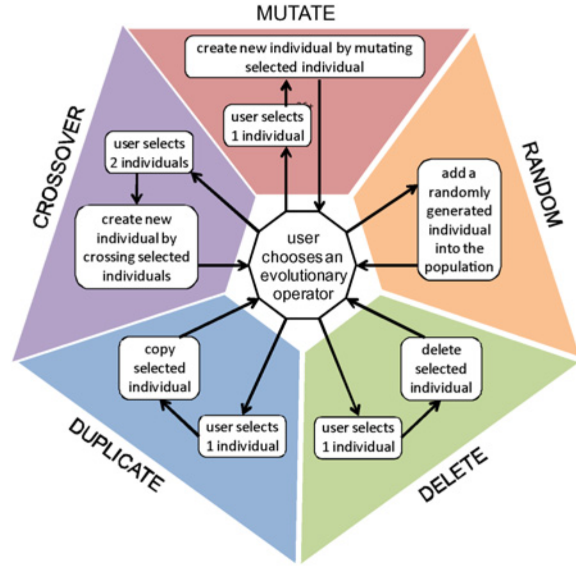

Fig. 2. Control flow of an HIEC application. Compare to Fig. 1.

II. Hyperinteractive Evolutionary Computation

We present HIEC as a novel form of IEC where a human user has all available evolutionary operators at his/her disposal. The control structure of an HIEC algorithm is illustrated in Fig. 2. The user directs the overall search process and initiates actions by choosing when and how each evolutionary operator is applied. The user may add a new individual to the population through the crossover, mutate, duplicate, or random operators. The user can also remove individuals with the delete operator. This naturally results in dynamic variability of population size and continuous generation change (like steady-state strategies for genetic algorithms [4]).

In HIEC, the user can wield evolutionary operators like tools, using each to impart a different kind of specific change to a subset of the evolving population of individuals, just as a painter uses a variety of brushes and paints to impart different kinds of change to the developing canvas. In this sense, working with an HIEC system is somewhat similar to working with typical interactive editing applications.

It is instructive to compare the control flow of NIEC (Fig. 1) to that of HIEC (Fig. 2). In NIEC, the user inhabits a single node in a simple periodic sequence, while in HIEC, the user inhabits the central node or hub of the system as well as many of the lower level nodes. Moreover, while NIEC is characterized by abrupt changes from one generation to the next, the population in an HIEC changes more gradually, with only a small number of individuals being added or deleted at any given time. While gradual population changes in the (non-interactive) evolutionary computation literature abound, HIEC is the first example of an IEC framework to use this technique.

There is another important difference between HIEC and NIEC. While NIEC requires that the user explicitly supply fitness information to the system, no such mechanism for obtaining fitness information from the user exists in HIEC. This is because in HIEC it is the human, not the computer, who decides when and how to perform selection.

HIEC follows in the footsteps of other IEC technologies that have successfully increased the role of the user beyond that of fitness evaluator. IEC technologies which are designed to increase the participation of the user have collectively been referred to as "active user intervention (AUI)" [5]. One conceptual leap we attempt to achieve with HIEC is to have the human user not just "intervene" with a search process driven primarily by a computer, but play a more central role as the main driver of the search process (as seen in Fig. 2), where the computer merely assists the user's active design efforts by providing evolutionary operators.

In what follows, we discuss four existing AUI technologies and their relationships with HIEC. Specifically, we will discuss SBART with multi-fields [6], [7], online knowledge embedding [8], visualized IEC [5], and human based genetic algorithms (HBGA) [9].

SBART version 2.2b [7] has a multi-field interface which allows users to create distinct subpopulations (fields) of individuals. Each field is contained within its own separate window and is evolved independently by the user. The user may also elect to copy individuals from one field to another. In addition, SBART 2.2b features context menus which can be used to apply evolutionary operators directly to a selected individual in a manner that is very similar to HIEC. While we find the "multiple fields" aspect of the SBART 2.2b interface to be commendable in its own right, it is the ability to apply evolutionary operators directly to selected individuals which we feel is the more fundamental design innovation, and is the reason we see the SBART 2.2b interface as a forerunner of HIEC. Technical differences of SBART 2.2b compared to our HIEC are that it still uses discrete generation changes in each field and it does not allow the user to browse the entire population on a screen at once.

Online knowledge embedding [8] allows the user to submit search ideas, hints, or intentions to make the search more efficient, e.g., the user cuts down the search space by fixing genes in real time. Online knowledge embedding is most effective in non-epistatic search spaces, i.e., search spaces in which each gene contributes independently to the phenotype of an individual. HIEC contains no such limitation and is well suited for epistatic search spaces with many gene-gene interactions. Conversely, online knowledge embedding is likely to converge much quicker than HIEC when used on non-epistatic search spaces, due to the large search regions that are ruled out each time a gene is fixed.

Visualized IEC [5] visualizes a multi-dimensional search space on a 2-D plane, allowing the user to visually grasp the entire distribution of individuals. This allows the user to provide a rough estimate of the location of the global optima to the system. The construction of a visualized IEC system requires that a meaningful mapping from the multi-dimensional search space to the 2-D plane be identified. Such a mapping must approximately preserve the topological relationships that exist among the individuals [5]. In the event that an appropriate mapping cannot be identified, HIEC can still be employed. On the other hand, visualized IEC can be integrated into EC algorithms in which fitness information is provided by the computer rather than by a human. In such cases, visualized IEC can accelerate the convergence of the EC search [5]. HIEC does not have the capability to work with computer-supplied fitness data.

HBGA [9] is a genetic algorithm in which the low-level execution of evolutionary operators is outsourced to one or more human agents. This approach is particularly useful for cases in which the representation of the evolving entities is not well defined. For example, a human agent may be prompted to mutate an idea which has been expressed in natural language.[1] On the other hand, HBGA is not well suited for problems in which the low-level execution of evolutionary operators is not easy or obvious to humans.

To illustrate the relationship of the online knowledge embedding, visualized IEC, and HBGA technologies to our HIEC, we partition the search control into the following three levels. The top level is *global settings*, where global variables such as population size and mutation rate are defined. This level also contains information about the search space and estimations of the global optimum within it. Next is the *population level*, where changes to the population are executed using individual evolutionary operators as minimal operational units. The last one is the *individual level*, where individuals are actually modified and their resulting fitness is ascertained. By considering the levels of user-driven search control that each technology emphasizes (Fig. 3), it is clearly realized that the relationships between those technologies and our HIEC are complementary, rather than mutually exclusive. The architectures of future IEC applications therefore may have a larger set of interaction-enhancing features. The appropriateness of each feature will likely be problem specific.

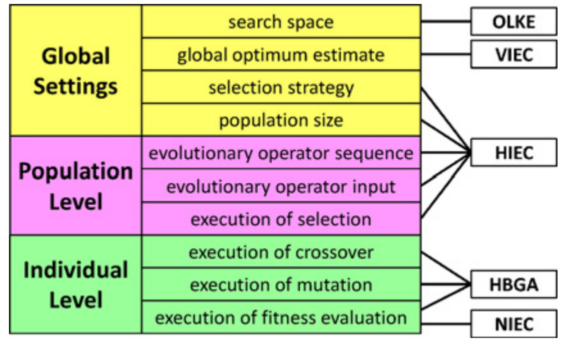

Fig. 3. Levels of search control granted to the user by online knowledge embedding (OLKE), visualized IEC (VIEC), HIEC, HBGA, and NIEC. As shown in this figure, these technologies are not mutually exclusive and can therefore complement each other.

III. Experiments

In this section, we present three human-subject experiments and their results that demonstrate the benefits and potentials of HIEC. For the experiments, we developed and used two software applications, Swarm Chemistry 1.1 and 1.2, which are NIEC and HIEC applications, respectively. This approach is similar to the one taken in [10], where several different interaction mechanisms for an IEC application were compared.

A. Swarm Chemistry

Swarm Chemistry [11], [12] is a novel artificial chemistry [13] framework that uses artificial swarm populations as chemical reactants and designs spatio-temporal patterns of heterogeneous swarms using IEC. In Swarm Chemistry, it is assumed that self-propelled particles move in a 2-D infinite continuous space. Each particle can perceive the relative positions and velocities of other particles within its local perception range, and changes its velocity in discrete time steps according to kinetic rules similar to those of Reynolds's Boids [14]. Each particle is assigned its own kinetic parameter settings that specify preferred speed, local perception range, and strength of each kinetic rule. Particles that share the same set of kinetic parameter settings are considered to be of the same type. For more details of the model and the simulation algorithm used, see [12]. The Swarm Chemistry simulators were implemented as Java applets/applications and are available online from the project website.[2] Using the simulators, one can interactively investigate what kind of dynamic patterns or motions may emerge out of the mixtures of multiple types of particles. Computational exploration has shown that heterogeneous particle swarms usually undergo spontaneous mutual segregation, often leading to the formation of multilayer structures, and that the aggregates of particles may additionally show more dynamic macroscopic behaviors, including linear motion, oscillation, rotation, chaotic motion, and even complex mechanical or biological-looking structures and behaviors. Specifications of those patterns were indirectly and implicitly woven into a list of different kinetic parameter settings and their proportions, called a recipe, which would be hard to obtain through conventional design methods but can be obtained heuristically through IEC methods.

Swarm Chemistry 1.1 [12] uses discrete, non-overlapping generation changes, like most other NIEC applications. The user selects one or two favorable swarms out of a fixed number of swarms displayed, and the next generation is generated out of them, discarding all other unused swarms (Fig. 4). Selecting one swarm creates the next generation using perturbation and mutation. Selecting two swarms creates the next generation by mixing them together (similar to crossover, but this mixing

[1] For example, see the Free Knowledge Exchange Project (http://3form.org).

[2] Available at: http://bingweb.binghamton.edu/~sayama/SwarmChemistry.

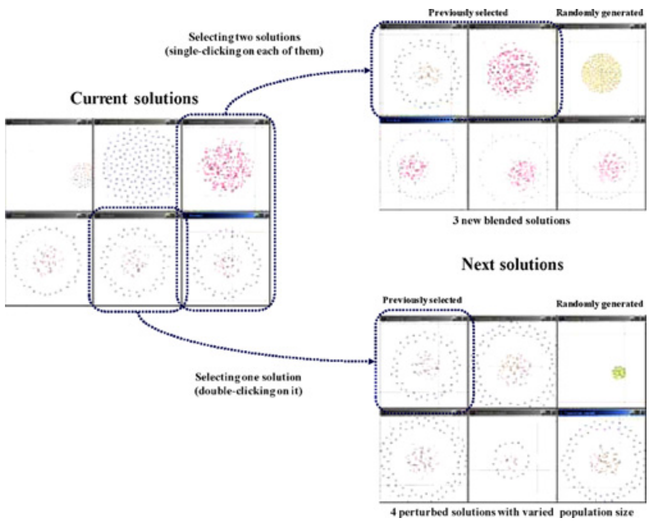

Fig. 4. Selection operations and consequent generation changes in Swarm Chemistry 1.1. A next generation is produced using only a few swarms selected by a user, while unselected ones are discarded.

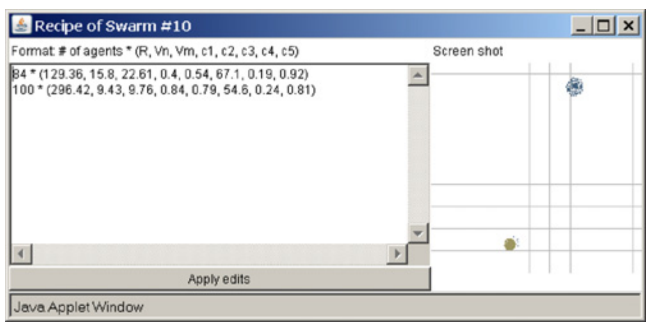

Fig. 5. Recipe window showing the composition of different types of particles in a swarm.

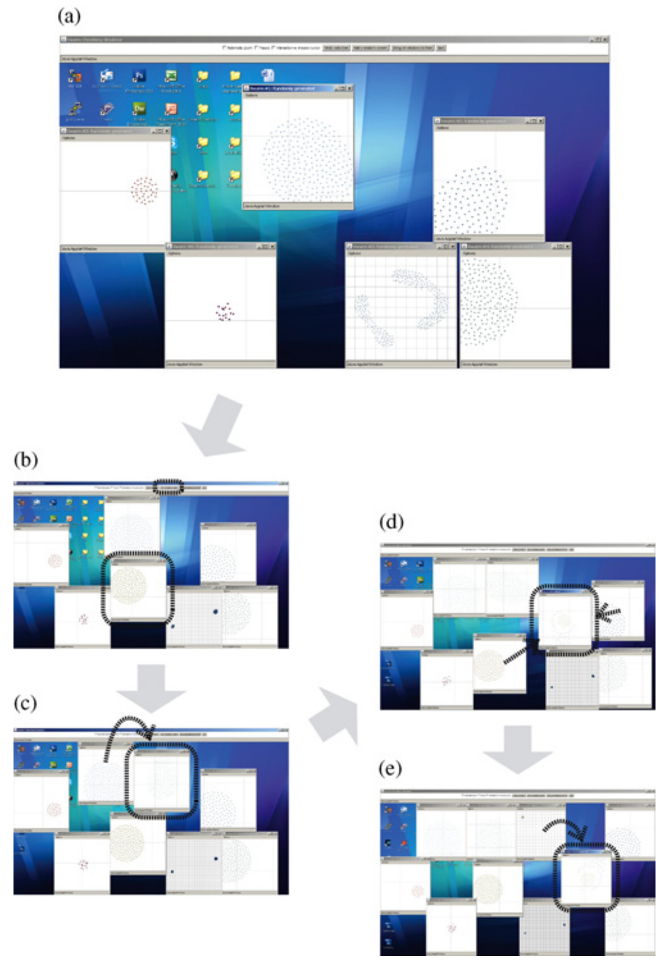

Fig. 6. Demonstration of how Swarm Chemistry 1.2 works. (a) Screenshot. Multiple swarms are displayed at random positions on a screen and simulated simultaneously. Positions and sizes of the frames are adjusted automatically using simple pseudo-kinetic rules. The long rectangular frame at the top is the control panel. (b) Random generation. Clicking on the "add a random swarm" button in the control panel adds a new, randomly generated swarm at a random position on the screen. (c) Mutation. Selecting the "mutate" option or double-clicking on a frame creates a mutated copy of the selected swarm next to it. (d) Mixing. Selecting the "mix" option or single-clicking on two frames creates a mixture of the selected two swarms between them. (e) Replication. Selecting the "replicate" option on a frame creates an exact copy of the selected swarm next to it.

is not genetic but physical). Right-clicking on a swarm opens a recipe window (Fig. 5), where the user can see how many particles of each type are used in simulating that swarm.

Swarm Chemistry 1.2 [15] has a redesigned HIEC-based interface with the same simulation algorithm of a swarm's kinetic dynamics as its NIEC counterpart. Fig. 6(a) shows a screenshot of version 1.2, where multiple swarms are displayed in separate frames placed at random positions on a screen and simulated simultaneously. Each frame has a set of evolutionary operators in its menu (Fig. 7, redesigned from the one published in [15]). In version 1.2, the number of swarms is unlimited and changes dynamically in the course of interactive design. Positions and sizes of the frames are automatically adjusted using simple pseudo-kinetic rules, though they can be changed manually too.

Version 1.2 uses continuous generation changes, i.e., each evolutionary operator is applied only to part of the population of swarms on a screen without causing discrete generation changes [Fig. 6(b)–(e)]. A randomly generated swarm can be added by clicking on the "add a random swarm" button in the control panel located at the top [Fig. 6(b)]. A mutated copy of an existing swarm can be generated by either selecting the "mutate" option or double-clicking on a frame [Fig. 6(c)]. Mixing two existing swarms can be done by single-clicking on two frames, one after the other. Mixing can also be performed by selecting the "mix" option on each of the two frames, one after the other. The new mixture is placed physically in the middle of the two selected swarms' frames [Fig. 6(d)]. The "replicate" option creates an exact copy of the selected swarm next to it [Fig. 6(e)]. The "edit" option opens a recipe window of the selected frame (Fig. 5), where the user can see and edit the kinetic parameter sets of the swarm directly. Finally, one can remove a frame from the population by selecting the "kill" option or simply closing the frame (example not shown in figures).

For the remainder of this paper, we will refer to Swarm Chemistry 1.1 as "the NIEC application" and Swarm Chemistry 1.2 as "the HIEC application." Further, we will use the word "designs" to refer to the swarms created using these applications.

Fig. 7. Menu available on each frame in Swarm Chemistry 1.2.

B. Experiment 1: User Experience

In the first experiment, we evaluate the benefits of HIEC in terms of user experience, such as intuitiveness, fun, controllability, and fatigue. Of particular concern in the IEC research is the user fatigue issue [1] because it limits the exploratory capability of the interactive search processes. In NIEC, since the user serves as a fitness evaluator, user fatigue is typically considered to be proportional to the amount of fitness information provided by the user during an IEC run. In HIEC, however, the user takes an active role in the overall search, which makes it difficult to characterize user fatigue simply by the amount of fitness information provided by the user. Therefore, we used the subjects' self-reports to a questionnaire as a method to assess the fatigue level perceived by the user.

1) *Experimental Setup:* The subjects were recruited from students and faculty/staff members at Binghamton University, Binghamton, NY. The subjects' backgrounds were: 9 females, 12 males; 15 students, 5 faculty/staff members, 1 other; 10 from the School of Engineering and Applied Science, 11 from others. Each subject was recruited and participated individually. Upon agreeing to participate in the study, the subject was told that he or she was to spend 5 min using each of two applications to design an "interesting and lifelike" design. The two applications, "Platform X" and "Platform Y," were the NIEC and HIEC applications, respectively. Since subjects were not familiar with the applications, subjects were given brief tutorials on their usage. Each of these two applications ran on their own dedicated computer station.

Subject participation proceeded as follows.

a) The subject was seated at one of the two stations and given 5 min to design an "interesting and lifelike" design using the platform installed on that station (either NIEC or HIEC).
b) The subject was then moved to the other station and given 5 min to design an "interesting and lifelike" design using the platform installed on that station.
c) The subject filled out a survey, rating each of the two platforms on the following factors: easiness of operation, controllability, intuitiveness, fun factor, fatigue level, final design quality, and overall satisfaction. Each factor was rated on a 5-point scale.

To avoid order bias, the orders of platforms used in steps 1 and 2 were varied. Furthermore, the positions of the two stations were varied between left and right so as to minimize bias that might result from their physical positions. As a result, four subjects participated under the X(left)→Y(right) configuration, four subjects under the Y(right)→X(left) configuration, five under the X(right)→Y(left) configuration, and six under the Y(left)→X(right) configuration.

TABLE I
DIFFERENCES IN USER EXPERIENCE OBTAINED IN EXPERIMENT 1

Factor	Median NIEC Rating	Median HIEC Rating	Two-Sided *p*-Value
Easiness of operation	5	5	0.681
Controllability	**3**	**5**	$<$ **0.0001***
Intuitiveness	4	4	0.280
Fun factor	**4**	**5**	**0.007***
Fatigue level	1	2	0.737
Final design quality	4	4	0.184
Overall satisfaction	**4**	**5**	**0.009***

* Significant differences are shown in bold and marked with an asterisk.

2) *Results:* The rating data was analyzed for differences in user experience using the Wilcoxon Rank-Sum test. In this and all the following statistical tests, the significance level $\alpha = 0.05$ was used. A summary of the results is given in Table I. Of the seven factors measured, three showed a statistically significant difference between two platforms: controllability, fun factor, and overall satisfaction. The higher controllability ratings for HIEC suggest that our original intention to re-design an IEC framework to grant greater control to the user was successful. Our results also suggest that this increased control may be associated with a more positive user experience, as is indicated by the higher overall satisfaction and fun ratings for HIEC. In addition, we did not find a statistically significant difference in fatigue level between NIEC and HIEC, contrary to what we originally expected. In the meantime, there was no significant difference detected in terms of perceived final design quality either. This issue is investigated in the next experiment.

C. Experiment 2: Design Quality

The goal of the second experiment was to quantify the benefit of HIEC over NIEC in terms of final design quality. In addition, the effects of mixing and mutation operators on the final design quality were also studied. The key feature of this experiment was that design quality was rated not individually by the subjects who designed them but simultaneously by an entire classroom full of subjects. The increased amount of rating information yielded by this procedure allowed us to more effectively detect differences in quality between designs created using NIEC and designs created using HIEC.

1) *Experimental Setup:* The experiment was done as part of the activities in the "Evolutionary Product Design" module of an engineering elective course "Exploring Social Dynamics," which was developed with financial support from NSF (Award 0737313) and offered to senior and junior bioengineering and management majors at Binghamton University. The participating students' backgrounds were: 9 females, 12 males, 18 bioengineering major, 3 management major. Those subjects did not have any overlap with the subjects of experiment 1.

The procedure of the experiment was as follows.

a) 21 students were randomly divided into seven groups, each made of three members. Every time groups were formed, we confirmed that each group had at least one member who had a Java-enabled laptop computer with wireless network connection.

b) They were instructed to launch the NIEC application from the project website, received a brief explanation of how to use the application, and then asked to work together as a team to design an "interesting" design within 10 min. After that, each group was reminded to make a final decision within an extra minute and choose the best design as the group's final design. Then they were told to post their designs to an online bulletin board. This step is called "condition 0" hereafter.

c) Then, the HIEC application was introduced with a brief explanation of how to use it and how it differs from the NIEC version, and the following four conditions were disclosed to the students: 1) baseline (neither mixing nor mutation operators available); 2) mixing only; 3) mutation only; 4) mixing + mutation (full-featured HIEC).

Correspondingly, four variations of the new simulator were prepared and uploaded to the website, each of which was configured with these two evolutionary operators enabled or disabled according to the experimental condition associated with it.

d) Students were randomly reshuffled into seven new groups. Each group was randomly assigned to one of the above four conditions and told to launch the application that corresponds to the assigned condition. Then they were told again to collaboratively create a nice design within 10 min (Fig. 8) and post their final design to the online bulletin board within an extra minute.

e) The above step was repeated three times, making the total number of final designs $(1 + 3) \times 7 = 28$. Every time, the students were randomly regrouped so as to minimize potential effects of confounding factors. The total number of produced swarms are: condition 0: 7, condition 1: 5, condition 2: 5, condition 3: 5, condition 4: 6.

f) Finally, all 28 designs generated were displayed on a large screen in the classroom (Fig. 9). The order of the designs was randomized on the screen (except for those of condition 0 that were arranged on the top row for technical reasons). Then each student was told to evaluate how "cool" each design was on a 0-to-10 numerical scale (10 being the best) using a web-based rating system. For those who did not have a laptop, PDAs with wireless network connection were handed out as needed. As a result, each design received 21 individual rating scores.

2) *Results:* To quantify the differences in ratings across the different conditions, we sought to consolidate the individual student ratings to yield a "group rating" for each design. However, individual student rating patterns varied widely, with some students tending to rate near the extremes of the scale, and others near the center of the scale. In order to ensure that each student had an equal influence on the group rating for each design, it was necessary to transform the ratings given by each student so that the mean of each student's ratings was 0 and the standard deviation was 1. These "effective scores" were then collected and averaged for each of the five (0–4) experimental conditions. The result is shown in Fig. 10.

Fig. 8. Students working on collaborative swarm design tasks during the in-class experiment.

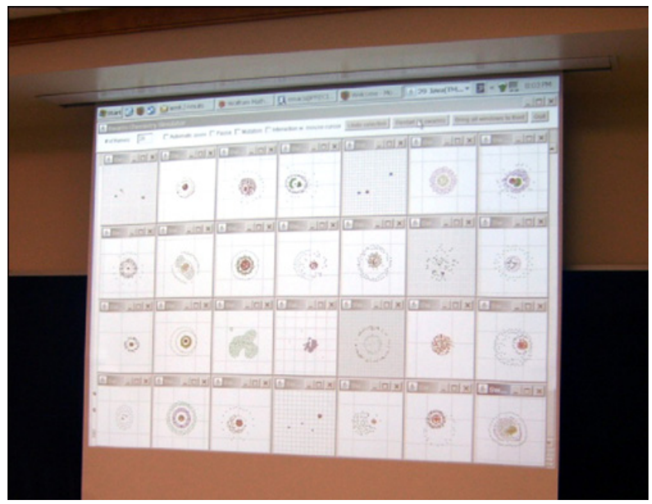

Fig. 9. 28 swarms simultaneously simulated and projected on a large screen in the classroom for students' group evaluation.

Several final designs produced through the experiment are shown in Fig. 11 (three with the highest scores and three with the lowest scores), which indicate that highly evaluated swarms tend to maintain coherent, clear structures and motions without dispersal, while those that received lower ratings tend to disperse so that their behaviors are not appealing to students.

To detect statistical differences between experimental conditions, a one-way ANOVA was conducted. The result of the ANOVA is summarized in Table II. Statistically significant variation was found between the conditions ($p < 0.005$). Tukey's and Bonferroni's post-hoc tests detected a significant difference between conditions 0 and 4, which supports our hypothesis that the HIEC is more effective at producing final designs of higher quality than NIEC. The post-hoc tests also detected a significant difference between conditions 1 and 4.

D. Experiment 3: HIEC for User Behavior Research

In experiments 1 and 2, we showed that HIEC has significant user experience and performance benefits over NIEC as an evolutionary design tool. In the third experiment, described

TABLE II
RESULTS OF ONE-WAY ANOVA ON THE RATING SCORE DATA FOR CONDITIONS 1-4 OBTAINED IN EXPERIMENT 2

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F	F-Test p-Value
Between groups	4	14.799	3.700	4.11	**0.003***
Within groups	583	525.201	0.901		
Total	587	540			

* Significant difference is shown in bold and marked with an asterisk.

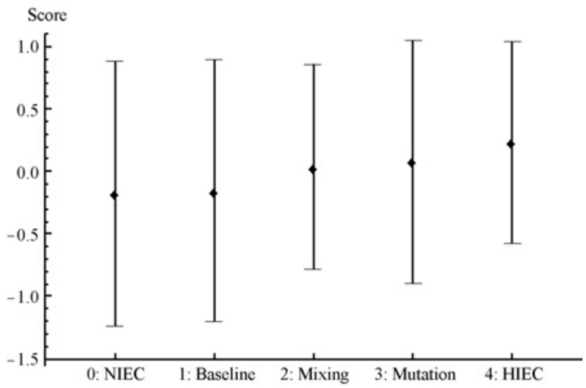

Fig. 10. Comparison of effective score distributions between products produced under five experimental conditions. Conditions 1, 2, and 3 are limited versions of HIEC. Mean effective scores are shown by diamonds, with error bars around them showing standard deviations.

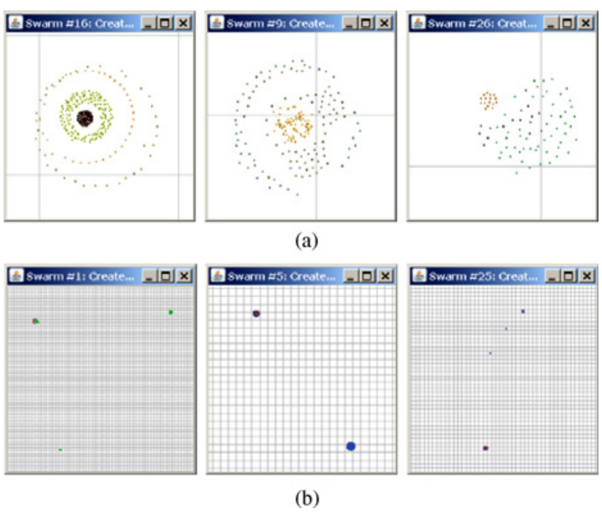

Fig. 11. Samples of the final product designs created by students. (a) Best three that received the highest rating scores. They were produced under condition 3, 4, and 4 (from left to right), respectively. (b) Worst three that received the lowest rating scores. They were produced under condition 0, 0, and 2 (from left to right), respectively.

in this section, we further explore and demonstrate other possibilities of HIEC, specifically as a data collection tool for user behavior research. Specifically, we provide subject groups with different priming instructions ("creative," "critical," and "control") and measure, using a modified HIEC application, how each of the instructions affects the group's behavior.

1) *Experimental Setup:* The experiment was again conducted as part of the "Exploring Social Dynamics" course mentioned earlier. The participating students' backgrounds were: 6 females, 16 males; 12 bioengineering major, 10 other majors. This experiment was done in a different semester from that of experiment 2 so the subjects did not have any overlap with the subjects of experiment 1 or 2.

Fig. 12. Students using the touchscreen PCs to design products with the HIEC application.

To collect data of evolutionary events during design processes, we revised the HIEC application so that it could keep track and generate a complete time-stamped log of all the evolutionary events taking place within an HIEC run. This modified application was then used simultaneously by a group of collaborating subjects. In addition, for this experiment we decided to use a new touchscreen-based digital tabletop interface, which has proved to be more suited to collaborative work than their mouse-monitor counterparts [16], [17].

Since the price of commercial digital tabletops, such as Microsoft Surface or Mitsubishi Electronics' DiamondTouch, is currently in the tens of thousands of dollars [18], we improvised a more economical alternative by using small touchscreen PCs. Specifically, we used the "Asus Eee Top" touchscreen PC available for only $500. When placed on its side with the screen facing up, it emulates the functionality of a digital tabletop. Once arranged in this way, up to four students can stand around the digital tabletop and interact with the HIEC application simultaneously.

The procedure of the experiment was as follows.

a) 22 subjects were placed into 6 groups of 3 and 1 group of 4 students each. Each group was assigned to a station with a digital tabletop running the modified HIEC application. The students were then given a brief tutorial on how to use the application, including an overview of the various evolutionary operators available to them. Each group was then given 10 min to design an aesthetically pleasing design (Fig. 12), with no further guidance given. This phase of the experiment served as the experimental control.

b) The subjects were reshuffled into seven new groups. Three groups were primed to be critical and risk-averse, with the following written instruction: "promote and maintain critical attitude throughout the design process. Incremental improvement of existing designs is the key to making a reliable solution. Completely new designs

TABLE III
TOTAL OPERATOR USAGE FREQUENCY ACROSS THREE CONDITIONS IN EXPERIMENT 3

Condition	Total Operator Usage Frequency			
	Mix	Mutate	Random	Replicate
Control	139 (62.9%)	48 (21.7%)	32 (14.5%)	2 (0.9%)
Creative	229 (66.2%)	50 (14.5%)	67 (19.4%)	0 (0.0%)
Critical	128 (40.6%)	168 (53.3%)	15 (4.8%)	4 (1.3%)

Relative frequency is shown in parentheses.

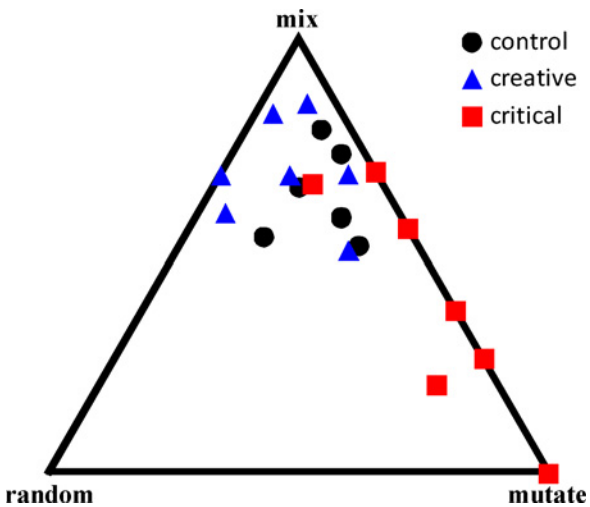

Fig. 13. Ternary plot of the user behavior data with respect to the mix, mutate, and random evolutionary operators. Each marker represents data taken from one group.

will never be better than well-tested ones." The other four groups were primed to be creative and adventurous, with the following written instruction: "Promote and maintain creative attitude throughout the design process. Crazy inspiration and idiosyncratic thinking is the key to breaking the barrier of stereotyped designs. Incremental improvement of existing designs will never work out." Then the groups were once again given 10 min to design an aesthetically pleasing design.

c) Step 2 was repeated, this time with four "critical" groups and three "creative" groups.

The log files containing detailed information about all the evolutionary events were saved to the local hard drive of each PC and later collected for post-experimental analysis. One of the "control" groups had a technical problem during the experiment, and therefore their data were excluded from the analysis. As a result, we collected data from six groups working under the "control" condition, seven under the "creative" condition, and seven under the "critical" condition.

2) *Results:* Table III shows a comparison among three conditions in terms of operator usage frequencies summed across all groups in each condition. The results indicate that control and creative groups behave essentially the same way, while critical groups exhibited a behavior that set them apart from the others. Fig. 13 is a ternary plot showing the distribution of relative operator usage frequencies of each group in a 2-D visualization space for three different conditions. Since the replicate operator was used so infrequently, it was excluded from this figure and subsequent tables. From the figure we can see that the control and creative groups appear to be clustered together near the mix corner of the triangle, while the critical groups are spread out over a much wider area.

TABLE IV
MULTIVARIATE TEST RESULTS OF ONE-WAY MANOVA ON OPERATOR USAGE FREQUENCY DATA FOR THE THREE CONDITIONS USED IN EXPERIMENT 3

Statistic	Value	F	Hypothesis df	Error df	F-Test p-Value
Pillai's Trace	0.586	3.524	4	34.000	**0.016***
Wilks' Lambda	0.416	4.410	4	32.000	**0.006***
Hotelling's Trace	1.402	5.258	4	30.000	**0.002***
Roy's Largest Root	1.399	11.894	2	17.000	**0.001***

* Significant differences are shown in bold and marked with an asterisk.

TABLE V
CONTRAST RESULTS (K-MATRIX) OF ONE-WAY MANOVA ON OPERATOR USAGE FREQUENCY DATA FOR THE THREE CONDITIONS IN EXPERIMENT 3

Contrast		Dependent Mix	Variable Mutate
Creative versus control	Contrast estimate	0.54	−0.095
	Hypothesized value	0	0
	Difference	0.54	−0.095
	Std. error	0.99	0.103
	Significance (p-value)	0.592	−0.369
Critical versus control	Contrast estimate	−0.245	0.344
	Hypothesized value	0	0
	Difference	−0.245	0.344
	Std. error	0.099	0.103
	Significance (p-value)	**0.025***	**0.004***

* Significant difference is shown in bold and marked with an asterisk.

We tested statistical differences between the conditions using MANOVA, a multivariate generalization of ANOVA, on the relative operator usage frequencies. The results are summarized in Tables IV and V, which is consistent with our statement that the control and creative populations are essentially the same while the critical population is distinct from the rest.

IV. CONCLUSION AND FUTURE WORK

In this paper, we introduced HIEC, a new class of IEC which extends the role of the user beyond that of the simple fitness evaluator commonly used in NIEC applications. We described three human-subject experiments. The first two experiments evaluate the advantages of HIEC over NIEC with respect to user experience and design quality, respectively. We found that users perceived HIEC to be more controllable, more fun, and more satisfying to use than NIEC. Furthermore, designs created using HIEC were of significantly higher quality than those created using NIEC. Our third experiment, which made use of an evolutionary event tracking feature, demonstrated the potential of HIEC as a scientific research tool for user behavior studies. We found that users will show different patterns of operator choices depending on the priming conditions given to them.

There are several limitations in each of the above experiments. First, we could not fully exclude several confounding factors in the experiments conducted in class, because they were part of the instruction and thus had to be delivered in a certain logical flow. For example, in the second experiment, condition 0 (NIEC) was tested prior to the other four conditions. Similarly, in the third experiment, the control condition was tested prior to the other two conditions. These non-random orders of conditions might have had influences on our experimental results. Second, and more importantly, all of our experiments used Swarm Chemistry as a testbed, so we cannot at this time be certain that the results derived by comparing the two applications (versions 1.1 and 1.2) are truly generalizable to other NIEC and HIEC applications. The possibility remains that the benefits of HIEC over NIEC may be problem dependent.

We also note that there are still several situations in which NIEC should be used rather than HIEC. First, NIEC is characterized by a rapid sequence of generations, each of which typically inherits characteristics from only one or two individuals of its parent generation. Hence, NIEC has a very high selection pressure and will converge quicker than HIEC. Thus, NIEC may be a useful option in situations where quick convergence is critical. Second, because the search strategy employed by an HIEC system is directed by the human user, it is likely that the performance of an HIEC system will depend strongly on the user's skill level. In particular, a user who understands the nuances of the exploration/exploitation tradeoff will likely perform better than a user who has never been exposed to evolutionary theory. In contrast, NIEC users act primarily as fitness evaluators, so that their evolutionary knowledge (or lack thereof) has no effect on the search trajectory. Thus NIEC should be used in situations where the system must perform consistently, regardless of the skill or educational background of the human user. Third, because HIEC gives the user the ability to control the number of individuals under consideration (i.e., the population size), it is possible that the user may allow the population to grow out of control. Since large populations are more difficult to manage than small ones, overpopulation may produce a computational and cognitive burden from which it is difficult to recover. NIEC, with its fixed population size, does not have this problem.

The following is a partial overview of some of the research we plan to do in the future to extend the quality and viability of HIEC applications.

A. Applications to Other Evolutionary Design Tasks

To address the generalizability issue mentioned above, we plan to develop other HIEC applications other than Swarm Chemistry. In experiment 1, we redesigned the interface of a non-HIEC application (in this case, Swarm Chemistry 1.1) to make an HIEC application (Swarm Chemistry 1.2). The same process can be applied to many other non-HIEC applications, as long as multiple individual designs can be visualized and displayed simultaneously on a monitor. For example, the non-HIEC applications for creating criminal suspect face sketches [19], 3-D computer graphics lighting designs [20], tiles [21], artwork [7], and virtual aquarium fish [22], [1] could each be redesigned as HIEC applications. The same set of human subject experiments that were done in this paper could then be conducted to check the robustness of our experimental observations across different tasks.

B. Computer-Assisted Selection Mechanism

In our current HIEC application, Swarm Chemistry 1.2, the user is responsible for manually pruning those individuals that he/she is no longer interested in. Some users found the process of deleting uninteresting individuals to be tedious, while preferring the use of more exploratory operators such as mixing and mutation. To take this burden off the user, we plan to implement a computer-assisted selection mechanism that detects which individuals the user is no longer interested in and automatically deletes them from the population. Specifically, individuals that the user has not interacted with for a long period of time will gradually begin moving toward the periphery of the display, until finally they simply "fall off" the screen and disappear. In addition, a "safe zone" will be provided near the center of the display, so that individuals that are dragged into it will be preserved indefinitely without continuous user interaction. These improvements may eliminate the burden of manual selection, thereby further decreasing user fatigue.

C. Integrating HIEC with Other Frameworks

Online knowledge embedding, visualized IEC, HBGA, the SBART 1.2 multi-field interface and HIEC were all designed to extend the role of the user beyond the role of fitness evaluator that he/she historically fulfills in NIEC. As indicated in Fig. 3, these frameworks are not mutually exclusive, so hybrids should be developed and examined. Future versions of HIEC applications could implement elements of online knowledge embedding, for example, by giving the user the ability to prune the search space.

Alternatively, elements of HBGA could also be implemented, for example, by allowing the user to directly manipulate and edit individual solutions.

D. Using Larger Tabletops

Although the exorbitant cost of large digital tabletop displays makes them inaccessible to most consumers, this is likely to be remedied in the future since technology tends to become cheaper over time. It may therefore be worthwhile investigating the use of large, multi-touch, multi-user digital tabletops by collaborative groups using an HIEC application. Such a system may provide the following benefits.

1) More individual designs can be displayed at the same time, which naturally improves the exploratory ability of IEC.
2) With multi-touch technology, group members need not waste time and energy taking turns.
3) With multi-user technology that enables identification of users, each group member's behavior can be tracked

separately, which will provide more detailed, useful data of user behavior.

4) Each group member can focus on exploring a subpopulation of the individuals displayed. Group members may occasionally "trade" individuals among themselves, leading to a search behavior similar to what is seen in course-grained distributed genetic algorithms [23].

Acknowledgment

The authors would like to thank S. D. Dionne, C. B. Laramee, and D. S. Wilson for their collaboration in conducting the in-class experiments for this paper, and also J. D. Schaffer for reviewing the draft and giving us many helpful comments.

References

[1] H. Takagi, "Interactive evolutionary computation: Fusion of the capabilities of EC optimization and human evaluation," *Proc. IEEE*, vol. 89, no. 9, pp. 1275–1296, Sep. 2001.

[2] P. Bentley and U.-M. O'reilly, "Ten steps to make a perfect creative evolutionary design system," in *Proc. GECCO Workshop Non-Routine Design with Evol. Syst.*, 2001 [Online]. Available: http://www.cs.usyd.edu.au/~josiah/gecco2001_workshop_schedule.html

[3] B. Shneiderman and C. Plaisant, *Designing the User Interface: Strategies for Effective Human-Computer Interaction*, 5th ed. Reading, MA: Addison-Wesley, 2009.

[4] D. Dumitrescu, B. Lazzerini, L. C. Jain, and A. Dumitrescu, *Evolutionary Computation*. Boca Raton, FL: CRC Press, 2000.

[5] N. Hayashida and H. Takagi, "Visualized IEC: Interactive evolutionary computation with multidimensional data visualization," in *Proc. IECON*, 2000, pp. 2738–2743.

[6] T. Unemi, "Simulated breeding: A framework of breeding artifacts on the computer," in *Artificial Life Models in Software*, M. Komosinski and A. Adamatzky, Eds. Berlin, Germany: Springer, 2009, ch. 12, pp. 271–392.

[7] T. Unemi, "A design of multi-field user interface for simulated breeding," in *Proc. 3rd Asian Fuzzy Syst. Symp.*, 1998, pp. 489–494.

[8] H. Takagi, "Active user intervention in an EC search," in *Proc. 5th JCIS*, 2000, pp. 995–998.

[9] A. Kosorukoff, "Human based genetic algorithm," in *Proc. IEEE Int. Conf. SMC*, vol. 5. Oct. 2001, pp. 3464–3469.

[10] A. M. Brintrup and H. Takagi, "The effect of user interaction mechanisms in multiobjective IGA," in *Proc. GECCO Conf. Companion Genet. Evol. Comput.*, 2007, pp. 2629–2632.

[11] H. Sayama, "Decentralized control and interactive design methods for large-scale heterogeneous self-organizing swarms," in *Proc. 9th ECAL*, 2007, pp. 675–684.

[12] H. Sayama, "Swarm chemistry," *Artif. Life*, vol. 15, no. 1, pp. 105–114, 2009.

[13] P. Dittrich, J. Ziegler, and W. Banzhaf, "Artificial chemistries: A review," *Artif. Life*, vol. 7, no. 3, pp. 225–275, 2001.

[14] C. W. Reynolds, "Flocks, herds, and schools: A distributed behaviorial model," *Comput. Graph.*, vol. 21, no. 4, pp. 25–34, 1987.

[15] H. Sayama, S. Dionne, C. Laramee, and D. S. Wilson, "Enhancing the architecture of interactive evolutionary design for exploring heterogeneous particle swarm dynamics: An in-class experiment," in *Proc. 2nd Symp. IEEE-CI-ALife*, Mar.–Apr. 2009, pp. 85–91.

[16] S. G. Koborov, K. Pavlou, J. Cappos, M. Stepp, M. Miles, and A. Wixted, "Collaboration with DiamondTouch," in *Proc. 10th IFIP TC13 INTERACT*, 2005, pp. 986–989.

[17] K. M. Inkpen, R. L. Hancock, and S. D. Scott, "Collaboration around a tabletop display: Supporting interpersonal interactions," Simon Fraser Univ., Burnaby, BC, Canada, Tech. Rep., 2001 [Online]. Available: http://pages.cpsc.ucalgary.ca/~msh/papers/inkpen-techreport2001.pdf

[18] C. Wolfe, J. D. Smith, and T. C. N. Graham, "A low-cost infrastructure for tabletop games," in *Proc. Conf. Future Play: Res. Play Share*, 2008, pp. 145–151.

[19] C. Cadwell and V. S. Johnston, "Tracking a criminal suspect through 'face-space' with a genetic algorithm," in *Proc. 4th ICGA*, 1991, pp. 416–421.

[20] K. Aoki, H. Takagi, and N. Fujimura, "Interactive GA-based design support system for lighting design in computer graphics," in *Proc. Int. Conf. Soft Computing (IIZUKA)*, 1996, pp. 533–536.

[21] C. Anderson, D. Buchsbaum, J. Potter, and E. Bonabeau, "Making interactive evolutionary graphic design practical," in *Evolutionary Computation in Practice*, T. Yu, L. Davis, C. Baydar, and R. Roy, Eds. Berlin/Heidelberg, Germany: Springer, 2008, ch. 6, pp. 125–141.

[22] T. Iwasaki, A. Kimura, Y. Todoroki, Y. Hirose, H. Takagi, and T. Takeda, "Interactive virtual aquarium (1st report)," in *Proc. 5th Annu. Conf. Virtual Reality Soc. Japan*, 2000, pp. 141–144.

[23] E. Cantú-Paz, "A survey of parallel genetic algorithms," *Calculateurs Parralèles, Réseaux et Systèmes Répartis*, vol. 10, no. 2, pp. 141–171, 1998.

Benjamin James Bush received the B.S. degree in mathematics from California State University, Long Beach, in 2007. He is currently pursuing the Ph.D. degree in systems science, as well as the Graduate Certificate in evolutionary studies.

He is currently a Graduate Research Assistant with the Collective Dynamics of Complex Systems Research Group, State University of New York at Binghamton, Binghamton. His current research interests include complex adaptive networks, social systems modeling and simulation, evolutionary computation, and theoretical computer science.

Hiroki Sayama (M'99) received the D.Sc. degree in information science from the University of Tokyo, Tokyo, Japan, in 1999.

He is currently the Director of the Collective Dynamics of Complex Systems Research Group and is an Assistant Professor with the Departments of Bioengineering and Systems Science and Industrial Engineering, State University of New York at Binghamton, Binghamton. He was a Post-Doctoral Fellow with the New England Complex Systems Institute, Cambridge, MA, from 1999 to 2002. He was an Assistant/Associate Professor with the University of Electro-Communications, Tokyo, from 2002 to 2005. His current research interests include complex dynamical networks, collective behaviors, social systems modeling, artificial life/chemistry, mathematical biology, and computer and information sciences.

Dr. Sayama is an Affiliate of the New England Complex Systems Institute, and is a member of the IEEE Computational Intelligence Society, the IEEE Computer Society, ACM, and several other professional societies.