Enhancing the Architecture of Interactive Evolutionary Design for Exploring Heterogeneous Particle Swarm Dynamics: An In-Class Experiment

Hiroki Sayama, Shelley Dionne, Craig Laramee and David Sloan Wilson

Abstract— **We developed Swarm Chemistry 1.2, a new version of the Swarm Chemistry simulator with an enhanced architecture of interactive evolutionary design for exploring heterogeneous self-propelled particle swarm dynamics. In the new version, each evolutionary operator acts locally and visually to part of the population of swarms on a screen, without causing entire generation changes that were used in earlier versions. This new architecture is intended to represent cognitive actions in human thinking and decision making processes more naturally. We tested the effectiveness of the new architecture through an in-class experiment with college students participating as designers as well as evaluators of swarms. We also measured the effects of mixing and mutation operators to the performance improvement of the design processes. The students' responses showed that the designs produced using the new version received significantly higher ratings from students than those produced using the old one, and also that each of the mixing and mutation operators contributed nearly independently to the improvement of the design quality. These results demonstrate the effectiveness of the new architecture of interactive evolutionary design, as well as the importance of having diverse options of action (i.e., multiple evolutionary operators in this context) in iterative design and decision making processes. This work also presents one of the few examples of human-involved experiments on the statistical evaluation of artificial lifeforms, whose quality (such as "livingness") would be hard to assess without using human cognition at this point.**

I. Introduction

INTERACTIVE EVOLUTIONARY COMPUTATION (IEC) is a powerful tool that can help humans design complex systems and solve complex problems in a huge search space where a utility function is ill-defined and fundamentally multi-objective [1], [2], [3]. In Artificial Life, IEC has been actively applied to the evolutionary design of artificial creatures and other kinds of objects, especially those with aesthetic properties [4], [5], [6], [7], [8], [9], [10], [11]. We also applied IEC to the design of homogeneous [12] and heterogeneous swarms [13], [14] in the past.

We note that IEC can be not just a practical tool for design and problem solving tasks but also a scientific tool for representation and visualization of real human decision making dynamics. We proposed in [15], [16] that human decision making may be redefined as evolution of ecologies of ideas being discussed, where populations of potential solutions evolve via continual applications of evolutionary operators, and that several cognitive actions in human decision making may be mapped to those operators, such as advocacy (replication), criticism (removal), minor modification (point mutation), integration (recombination), and sudden inspiration (random generation). This analog implies that one could collect detailed information about human decision making dynamics by conducting experiments with human subjects using appropriately configured IEC tools. We have been working on the implementation of such experiments based on our earlier work on interactive design of heterogeneous swarms.

One fundamental limitation in our earlier IEC-based swarm design system is that it used non-overlapping generation changes with a small number of selected parent swarms. Namely, a human designer chooses a few favorable swarms from a population and then the next generation will be generated almost entirely from those selected swarms, while most of the swarms that were not selected will be discarded. This scheme, called *simulated breeding* [1], [6], is often employed in IEC applications [4], [6], [13], [14] because it helps reduce the cognitive burden on the designer by decreasing the number of solutions the designer needs to evaluate at a time. However, it also significantly limits the exploratory capability of the evolutionary process, and more importantly, such discrete generation changes of idea populations may not necessarily capture the nature of real human decision making. People usually keep many different ideas in mind consciously or unconsciously at a time, and it is more reasonable to assume that cognitive actions tend to change those ideas more gradually and locally, instead of completely wiping most of them out at once.

To better represent such a gradual, continuous stream of human decision making, we have redesigned the architecture of the Swarm Chemistry simulator. In its new version, Swarm Chemistry 1.2, the evolutionary operators (such as replication, mutation and mixing) act locally and visually on the swarm(s) a designer selects, with no discrete generation changes. Due to this change, the population of swarms on a screen is expected to be more natural and accurate as a representation of the state of design possibilities in the designer's mind. We hypothesized that this enhanced new architecture would improve the performance of the IEC-

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based swarm design processes. To test this hypothesis, we designed and conducted an in-class experiment with college students participating as designers as well as evaluators of swarms. This paper presents a first report of this experiment, whose results seemed to indicate that the enhanced architecture indeed had a significant impact on the quality of final products.

The rest of the paper is structured as follows. In the next section, the technical details of the Swarm Chemistry simulator will be explained with a particular focus on what kind of changes have been implemented to the new version 1.2. Then the objective and procedure of the in-class experiment will be explained in Section III. The experimental results and statistical analyses on them will be presented in Section IV, followed by discussions and conclusions in Section V.

II. Swarm Chemistry 1.2

Swarm Chemistry [13], [14] is a novel artificial chemistry [17] 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 two-dimensional infinite continuous space. Each particle can perceive only the local center of mass and the average velocity vector of other particles within its local perception range, and change its velocity in discrete time steps according to kinetic rules similar to those of Reynold's Boids [18]. Each particle is assigned with 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 of the same type. For more details of the model and the simulation algorithm used, see [13], [14].

The Swarm Chemistry simulator was implemented as a Java applet/application and is available online from the author's website[1]. Using the simulator, 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 *recipe*, which would be hard to obtain through conventional design methods but can be obtained heuristically through IEC methods.

The earlier versions of the Swarm Chemistry simulator (1.0 [13], 1.1 [14]) used discrete, non-overlapping generation changes (Fig. 1), where a user selects only one or two favorable swarms and the next generation will be generated out of them, discarding all other unused swarms. In addition,

[1]http://bingweb.binghamton.edu/~sayama/SwarmChemistry/

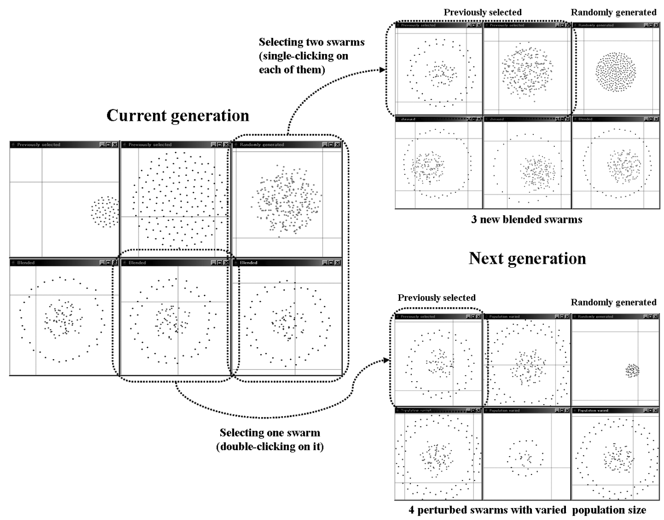

Fig. 1. Selection operations and consequent generation changes in the *old* version of the Swarm Chemistry simulator (version 1.0/1.1; figure taken from [14]). A next generation is produced using only a few swarms selected by a user, while unselected ones are discarded.

those old versions used a fixed number of swarms in each generation (though it was changeable manually in version 1.1). Moreover, the mutation operator became available only in version 1.1 (which was optional by default), and all the design results reported so far in [13], [14] were produced using the mixing operator only.

To address the problems mentioned above, we developed a new version of the Swarm Chemistry simulator, version 1.2. While the simulation algorithm of a swarm's kinetic dynamics remains exactly the same as that of earlier versions, the algorithm and the user interface of IEC underwent a major redesign. Figure 2(a) shows a screenshot of the new simulator, 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 option menu (Fig. 3). 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. 2(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. 2(b)). A mutated copy of an existing swarm can be generated by either selecting the "Mutate" option or double-clicking on a frame (Fig. 2(c)). Mixing two existing swarms can be done by either selecting the "Mix" option or single-clicking on two frames, where the new mixture is placed physically in the middle of the two selected swarms' frames (Fig. 2(d)). The "Replicate" option creates an exact copy of the selected swarm next to it (Fig. 2(e)). The "Edit" option opens a recipe window of the

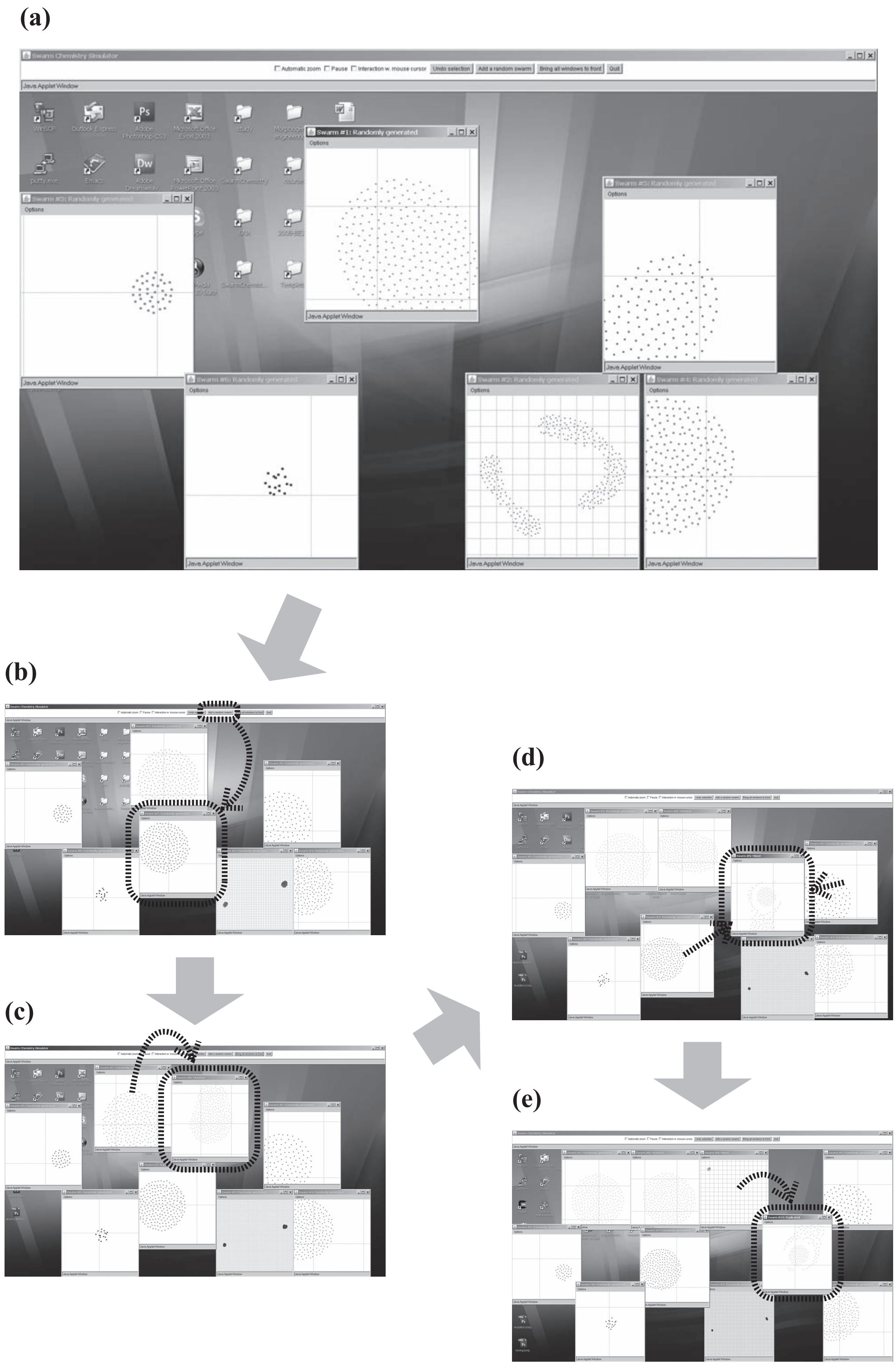

Fig. 2. A demonstration of how the *new* Swarm Chemistry simulator (version 1.2) works. (a) A screenshot. Multiple swarms are displayed at random positions on a screen and simulated simultaneously. Positions and sizes of the frames are adjusted automatically using simple pseudo-kinetic rules. The long 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.

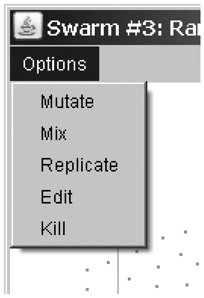

Fig. 3. An option menu available on each frame in the *new* version of the simulator (version 1.2).

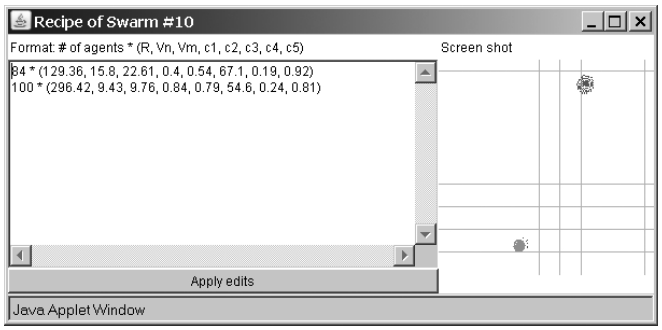

Fig. 4. A recipe window that opens when the "Edit" option is selected.

selected frame (Fig. 4), 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).

III. Experiment

To evaluate the new version of the Swarm Chemistry simulator, we conducted an in-class experiment in which college students participated as designers and then evaluators of swarms. The objective of this experiment was twofold: to examine if the new architecture of Swarm Chemistry 1.2 was more effective than that of the old versions, and to quantitatively evaluate how each of the evolutionary operators improved the overall "quality" of outcomes of evolutionary design. We specifically focused on mixing and mutation operators in this evaluation. The quality of swarms was measured by students' subjective peer evaluation.

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 in Fall 2008. The participating students' backgrounds were: 9 female, 12 male; 13 senior, 8 junior; 18 Bioengineering major, 3 Management major. This experiment was reviewed and approved by the Binghamton University IRB.

The procedure of the experiment was as follows.

1) 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.
2) They were instructed to launch the old version of the Swarm Chemistry simulator (version 1.1) from the author's website, received a brief explanation of how to use the simulator, and then asked to work together as a team to design an "interesting" swarming pattern within ten minutes. After that, each group was reminded to make a final decision within an extra minute and choose the best swarm design as the group's final product. Then they were told to open its recipe window and copy and paste its recipe text to an online bulletin board. This step is called "condition 0" hereafter.
3) Then, the new version of the simulator was introduced with a brief explanation of how to use it and how it differs from the old 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 new simulator)

   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.
4) Students were randomly reshuffled into new seven groups. Each group was randomly assigned to one of the above four conditions and told to launch the simulator that corresponds to the assigned condition. Then they were told again to collaboratively design a nice swarming pattern within ten minutes (Fig. 5) and post their final product to the online bulletin board within an extra minute.
5) The above step was repeated three times, making the total number of final products $(1+3)\times 7 = 28$. 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.
6) Finally, all the 28 swarms generated from the 28 submitted recipes were simulated simultaneously and projected to a large screen in the classroom (Fig. 6). The order of the swarms 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 swarm 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 swarm received 21 individual rating scores.

Fig. 5. Students working on collaborative swarm design tasks during the in-class experiment.

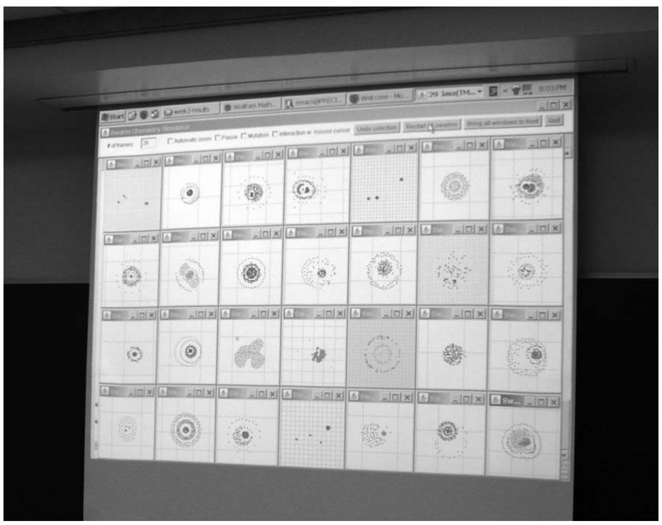

Fig. 6. 28 swarms simultaneously simulated and projected on a large screen in the classroom for students' peer evaluation.

IV. RESULTS

Students' evaluation results were first normalized so that the mean was 0 and the standard deviation 1 for each individual student's responses, in order to equalize the contribution of each student's ratings to the overall statistics. Then the normalized scores were collected and averaged for each of the five (0–4) experimental conditions. The result is shown in Fig. 7. There appears to be a difference in the mean normalized scores between the old and new versions (conditions 0 and 4), and the scores are higher when more evolutionary operators are available. Figure 8 shows several final swarm designs produced through the experiment (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 quite appealing to students.

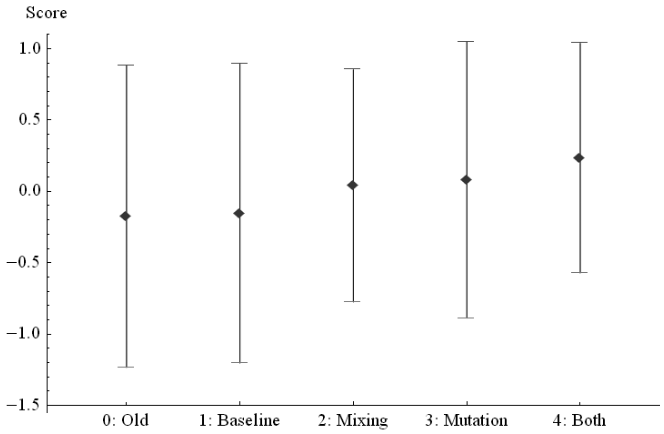

Fig. 7. Comparison of normalized score distributions between swarms produced under five experimental conditions. Mean normalized scores are shown by diamonds, with error bars around them showing standard deviations.

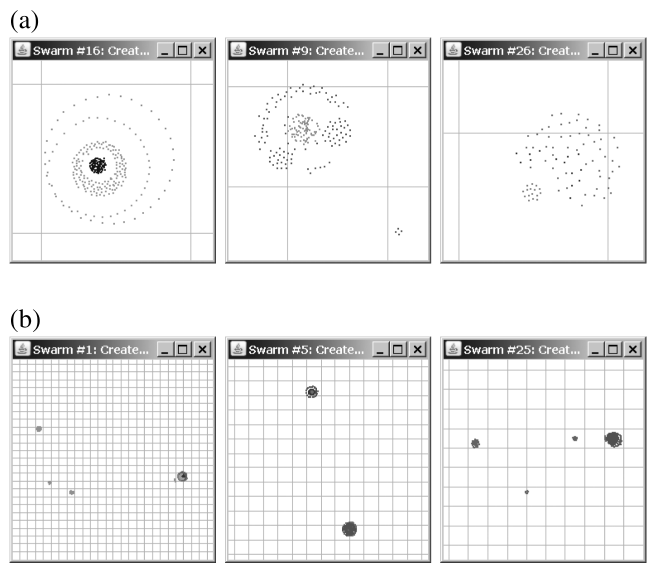

Fig. 8. Samples of the final swarm designs created by students. (a) The best three that received the highest rating scores. They were produced under condition 3, 4 and 4 (from left to right), respectively. (b) The worst three that received the lowest rating scores. They were produced under condition 0, 0 and 2 (from left to right), respectively.

To detect statistical differences between experimental conditions, the one-tailed Welch's t-test was conducted on each pair of the conditions. In this and all the following statistical tests, the significance level $\alpha = 0.05$ was used. The result of the t-test is summarized in Table I. A statistically significant difference was found between conditions 0 and 2–4, 1 and 3–4, and 2 and 4. In particular, a highly significant difference was detected between conditions 0 and 4 ($p < 0.0005$), which strongly supports our hypothesis that the newly developed architecture of Swarm Chemistry 1.2 is more effective in designing swarms than that of the old version.

In addition, the contribution of each evolutionary operator (mixing and mutation) was evaluated using 2×2 ANOVA applied to the data for conditions 1–4. The result is sum-

TABLE I

RESULTS OF ONE-TAILED WELCH'S t-TEST ON EACH PAIR OF THE FIVE CONDITIONS.

Condition X	Condition Y	p-value
0: Old	1: Baseline	0.438
	2: Mixing	**0.035**
	3: Mutation	**0.024**
	4: Both	**<0.0005**
1: Baseline	2: Mixing	0.068
	3: Mutation	**0.046**
	4: Both	**0.001**
2: Mixing	3: Mutation	0.370
	4: Both	**0.035**
3: Mutation	4: Both	0.099

TABLE II

RESULTS OF 2×2 ANOVA ON THE DATA FOR CONDITIONS 1–4.

Source of variation	Degrees of freedom	Sum of squares	Mean square	F	p
Mixing	1	3.671	3.671	4.443	**0.036**
Mutation	1	5.025	5.025	6.082	**0.014**
Error	438	361.9	0.826		
Total	440	370.6			

marized in Table II. A significant main effect was found for either of the two operators, mixing ($p = 0.036$) and mutation ($p = 0.014$). No significant interaction was noticed between these operators (Fig. 9). These results show that either operator significantly and independently contributed to the improvement of the quality of final products.

V. DISCUSSIONS

The experimental results shown above suggest that the revision of the architecture of interactive evolutionary design actually worked out well in improving the quality of the design outcomes as we originally intended. Our results also suggest that each of the mixing and mutation operators contributed nearly independently to the improvement of the design quality. This finding qualitatively agrees with our earlier work on computer simulation of collaborative decision making [16], where we discussed a possible relationship

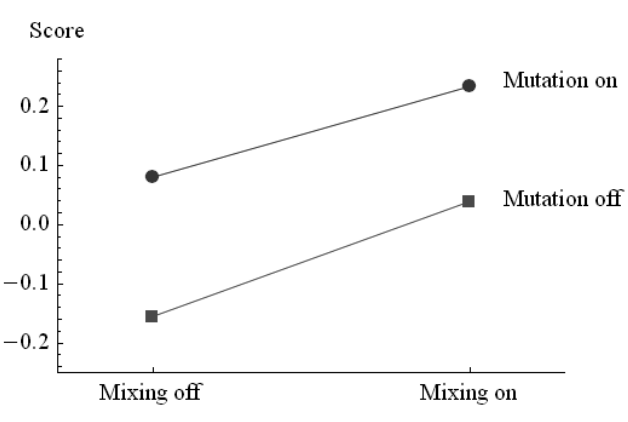

Fig. 9. Mean normalized scores plotted with regard to two sources of variation (mixing on/off and mutation on/off). Nearly parallel lines show that there is very little statistical interaction between the two operators.

between the performance of collective decision making and the behavioral patterns of participants in a group: the more diverse options of action they have in discussion, the better their collective decision making could be. In the experiment presented here, the availability of multiple evolutionary operators opens up new pathways to potentially better designs, improving the quality of final products on average.

Moreover, from the viewpoint of Artificial Life research, this work presents one of the few, unique examples of experimental studies involving human subjects on the statistical evaluation of artificial lifeforms. One of the main objectives of Artificial Life remains to define the "livingness" and other life-specific qualities of systems, which are hopelessly ill-defined concepts that are hard to assess without involving human cognition (at least at this point), and hence we believe that more human-involved experimental assessments of the qualities of "life-as-it-could-be" should be carried out in the field of Artificial Life. We hope that our work presented in this paper constitutes an illustrative example of such evaluation efforts.

We are aware of several limitations in the design of this experiment. As it was the very first experiment we conducted, we could not fully exclude several confounding factors due to technical reasons, which may have affected the results. Firstly, we had the students use their own laptops to participate in the experiment, so the difference in available computational power among them might have influenced the performance of interactive design. Secondly, since the condition 0 (the old version) was tested prior to the other four conditions, the students' learning over time may have negatively affected the scores for condition 0 (although this might well be cancelled by the effect of fatigue increasing over time). Thirdly, in all of the five conditions, the "Edit" option was not disabled, so there is small probability for some students to directly edit recipes of swarms to "intelligently" produce good designs. We tried to minimize the effects of those confounding factors by randomizing the groups before every session.

Other limitations in our experimental design include the fact that the effects of other operators (replication, removal, random generation) were not examined, and also that the mutation operator was actually a combination of several distinct mutation mechanisms (duplication, insertion and deletion of a parameter set within a recipe, and point mutation applied to specific parameter values) but their individual effects were not assessed separately either. However, increasing the number of experimental variables is one of the most difficult things to achieve in human-involved experiments like ours, because the time and efforts a human subject can spend in an experiment is generally limited.

Finally, we note that the proposed interactive evolutionary method works only for problems whose design criteria are easily visualized in small frames on the screen. It remains an open question whether the similar approach could be adapted to other design criteria that are not so easily visualized.

Despite those potential confounding factors and limitations, our experiment produced a reasonable result about the effects of the architecture (algorithm and user interface) and the availability of multiple evolutionary operators on the quality of IEC-based design and decision making. For future work, we plan to conduct an extended version of this experiment in which all the events during interactive evolutionary design will be recorded electronically so that more detailed information about the dynamics of human decision making and the effects of each individual evolutionary operator can be extracted from those data. It will be promising to do such experiments online so that an order-of-magnitude larger number of human subjects will be able to participate in the study, which will bear significant potential of applications as suggested in [9]. In addition, we also plan to conduct a more detailed analysis of the quantitative spatio-temporal properties of the "interesting" swarms evolved by students. Such analysis may provide insight into what "livingness" means to people.

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