Search Strategies and the Creative Process

Kyle E. Jennings

Institute of Personality and Social Research
University of California, Berkeley
jennings@berkeley.edu

Abstract. The human creative process can be likened to searching for solutions to a problem. This work introduces a computerized aesthetic composition task that is inspired by the "creativity as search" metaphor. Data from this technique can illuminate how personality and situational influences affect the creative process, rather than merely noting that they affect the outcome. Beyond this, the technique can be used to highlight underlying similarities between human creativity and optimization, as well as the important differences. Early results with $N = 34$ participants suggest that people's search strategies do differ, and show connections between personality, evaluation criteria, and search strategy. Suggestions for future research are given.

1 Introduction

The creative process can be thought of as the search for an ideal solution to a problem. One way to understand creativity is to understand this search process. This paper presents early results from a new behavioral research technique that is based on the creativity as search metaphor. In the short term, this technique will allow researchers to understand how individual di erences and situational in uences a ect the creative process, instead of merely noting that they a ect the outcome. In the medium term, the technique will be used to understand similarities and di erences between human creative search and optimization. In the long term, the hope is that this and related work will enable better communication among creativity researchers in the behavioral and computational traditions, eventually leading to a more integrative understanding of what creativity is and how it occurs.

The paper begins with a discussion of creativity and search. Then, the aims and design rationale for the new technique are presented, followed by illustrative results from an early application of the technique. Finally, future directions are discussed.

1.1 Creativity as Search

Search can either be seen as nding a path from a starting state to a speci c end state, or as nding the best solution from among many other solutions. The former case is relevant when the desired outcome is known but the means for achieving it are not (for example, proving a mathematical theorem). The latter case is relevant when the desired outcome is unclear, such as during the problem nding stages of the creative process. At least in the arts, creative people seem to be distinguished by the problems they choose to solve, not by how they solve them [1]. Accordingly, this research focuses on how people choose the best solution from among competing alternatives, and not on how that solution is realized.

In open-ended domains like the arts, choosing what solution to pursue is seldom a simple matter of deciding among a few known choices. Instead, the space of possibilities is usually too vast to be considered simultaneously, meaning that the search must proceed by iteratively considering subsets of the space. How people control this iterative process can be called a search strategy, and includes things like how people move from one subset to another, and how people evaluate each solution. Though search strategies might be an important determinant of how creative the search outcome is, they are not directly observable. However, if the options under consideration at each stage can be at least partially observed, it becomes possible to trace how people move through the space of possibilities over time. This path is called a search trajectory, and o ers clues as to what kind of search strategy people are using.

This research examines search trajectories, and characterizes them by how complex they appear to be, which is tantamount to how straight of a path people take from their starting solution to the solution they eventually settle upon. At rst blush simple trajectories might seem to re ect positive things like decisiveness and expertise. However, they may also re ect unsophisticated strategies that are not well-matched to the nature of the problem. This is particularly likely when the aspects of a solution that can be manipulated (the control dimensions) have complex relationships to the criteria that the solution is evaluated on (the evaluation dimensions). In these cases, simple strategies like repeatedly making incremental improvements until nothing can be improved upon can back re, since they might miss a drastically di erent solution that is far superior (see [2, 3]).

1.2 Instrument Design

As the foregoing suggests, a research instrument is needed that can track people s search trajectories. Because psychological studies involving personality and situational in uences often require large samples, this technique should be as economical to apply as possible, and should be simple to apply consistently across studies. Also, while high-resolution data are needed, they must be tractable enough to gain insights about as the technique is developed. All of this must be achieved without unduly straining the connection to creativity.

Existing creativity research techniques are not well-suited to these requirements. Table 1 characterizes insight tasks (e.g., [4, 5]), holistic assessment of end products (e.g., [6]), divergent thinking tests (e.g., [7]), and protocol analysis (e.g., [8]) according to whether they provide trajectory data, are economical to apply,

Instrument	Trajectory	Economical	Consistent	Tractable	Face Valid
Insight tasks	no	yes	yes	yes	mid[1]
Holistic assessment	no	mid	mid[2]	yes	yes[3]
Divergent thinking	possibly[4]	no	mid[5]	mid[4]	mid[1]
Protocol analysis	possibly[6]	no	possibly[6]	no	yes[3]
Exploration task	yes	yes	yes	yes	mid

1 — only represents one part of the creative process; 2 — while findings can be replicated across different tasks and raters, ratings can't be compared across samples; 3 — provided the task is a face valid creative task; 4 — with techniques under development (see [9]); 5 — norms available, but often not used; 6 — depending on how applied

Table 1. Comparison of creativity measurement techniques.

can be applied consistently, yield tractable data, and are face valid operationalizations of creativity. None of the techniques provides detailed trajectory data in an economical manner.

The technique developed here is a computerized aesthetic composition task. Participants have a fixed amount of time to explore a three-dimensional scene on the computer, with the goal of finding the image that most captures their interest.[1] Participants can manipulate two things: the camera position, and the position of a light source. However, because of the reflection, refraction, and shadows caused by the interplay of the materials and the light, the task is both less straightforward and more amenable to creative outcomes. (See Figs. 1, 3.)

The exploration task results in a moment-to-moment map of the search trajectory. Since there are only two control dimensions (camera and light angle), the search trajectory can be visualized to develop intuitions about the data. The task itself can be economically and consistently applied within typical psychological experimental conditions. Various metrics have been defined for analyzing the search trajectory (discussed later), with more sophisticated ones to be developed over time.

Perhaps the least satisfying aspect of the task is its relation to real-world creativity. However, nothing short of *in vivo* studies of working creators will give a perfect match. Laboratory tasks sacrifice this external validity in order to gain control. The exploration task encompasses more of the creative process than insight or divergent thinking tasks. While more constrained than typical tasks used with holistic assessments, the technique yields essential trajectory data.

Despite how constrained the task is, it is sufficiently complex to require more than ordinary problem solving. First, there is no single best solution. Instead, people will prefer different configurations based on the criteria they use, and would likely find that many configurations satisfied their criteria. Second, provided that people attend to the interplay among the materials in the scene, there is no simple relationship between the two control dimensions and the many eval-

[1] “Interest” incorporates aesthetic concerns [10] but admits more solutions than “aesthetically pleasing” without attracting merely odd solutions as “creative” might.

uation dimensions. If data visualization is not a major concern, more control dimensions can be added to increase the complexity.

2 Early Results

2.1 Methods

A preliminary experiment was run with $N = 34$ people, who participated in exchange for course credit. Though it is possible that the experiment description (perform an aesthetic composition task) attracted more aesthetically-oriented individuals, none of the participants majored in the arts.

After signing consent forms, participants were seated at a computer and instructed to begin the experiment, which proceeded automatically. To become familiar with the user interface, participants has up to two minutes to complete the exploration task using a simple scene consisting of a non-re ective, monochromatic arch on a checkered surface with a monochromatic sky. Next, they had up to ve minutes to complete the exploration task using the more complex scene shown in Fig. 1, with the goal of nding the image that most captured their interest. In both scenes, the camera and light were a constant distance from the center, with the angles adjustable in four degree increments. Participants could explore the 3D scenes by manipulating the camera and light angles using either a knob that could be rotated to any angle, or buttons that moved one step clockwise or counterclockwise. A timer showed the elapsed and remaining time, as well a button to press when nished. Participants could choose to continue before the time limit expired.

After the exploration task, participants rated their liking of a subset of images from the scene. Due to problems with this measurement, these data are not analyzed here. Participants then wrote a few sentences describing how they approached nding the image that most captured their interest. Finally, they completed four questionnaires in a random order (item order was also random). Overall personality was assessed using the Big Five Inventory (BFI) [11]. Cronbach s α for the Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness dimensions were .82, .79, .79, .91, and .84, respectively. Three additional scales were included, but since no relationships were found with these scales, they are not discussed. Participants were debriefed upon completion.

2.2 Results

Metrics The following metrics are used to characterize the search trajectory. Where applicable, care was taken to ensure that these metrics properly re ect the circularity of the coordinates.

Time Time elapsed between the rst movement and the last movement. The median time was 1:10 (minutes : seconds), and the lower and upper quartiles were 0:51 and 1:43, respectively. The maximum time was 2:55, indicating that the ve minute time limit was more than su cient.

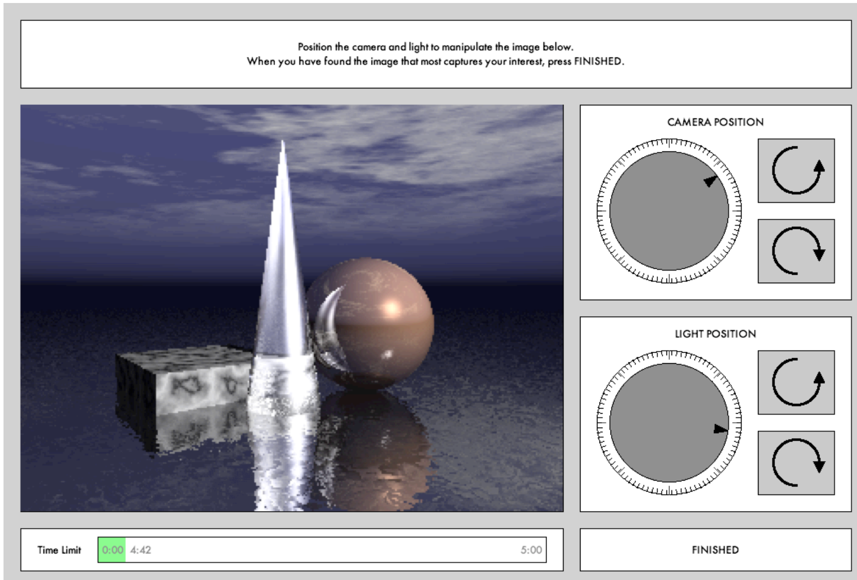


Fig. 1. Exploration interface, showing the experimental scene.

Coverage Percentage of the search space encountered, $M = 1.84\%$ and $SD = 0.70\%$. Unsurprisingly, each person explored only a small part of the space.

Fixations Number of points where the person lingered, determined by doing a Gaussian kernel density estimate over the time spent per coordinate ($\sigma_{11} = \sigma_{22} = 8$ degrees), and then counting the local maxima, $M = 15.8$, $SD = 5.75$.

Fixation Diversity The mean inter- xation point distance was calculated for the upper 50% of each trajectory s xation durations (which tended to be less similar to each other in duration than the lower 50%), $M = 117$, $SD = 16.6$.

Dimension Changes Times that the search switched control dimensions. Follows a Poisson distribution with $\lambda = 2.26$. The modal value was one, indicating that most people searched one dimension, and then the other.

Rate The average number of new views per second, $M = 3.09$ and $SD = 1.12$.

Reversals Time that a trajectory switches direction along a single dimension, $M = 10.56$ and $SD = 6.92$.

Additionally, the outcome of the search can be characterized by how unusual the nal point is, which will be called **unusualness**. The calculation is based on the average distance between the current search s nal point and every other search s nal point. To make unusualness more interpretable, the average distance is divided by the mean of the average distances, and the log (base 2) taken. The mean is approximately zero, though in principle it needn t be. The intercorrelations between the metrics are shown as part of Table 2.

Criteria and Complexity The key question is how complex people s searches are, and what determines their complexity. One source of complexity is the nature

	2	3	4	5	6	7	8	9	10	11	12	13
Metrics												
1. Total Time	.59***	.27	.08	.15	.37*	-.35*	-.11	-.02	.36*	.10	.20	.15
2. Coverage	—	.84***	.24	.59***	.51**	.30+	.22	.09	.46**	.27	.28+	-.05
3. Fixations		—	.32+	.67***	.47**	.37*	.33+	.22	.36*	.31+	.26	-.04
4. Fix. Diversity			—	.21	.21	.04	-.25	.23	-.04	.39*	.18	.07
5. Dim. Changes				—	.28+	-.00	.16	.31+	.10	.38*	.12	.02
6. Reversals					—	.32+	.42*	.03	.38*	.08	.38*	.16
7. Rate						—	.46**	-.05	.34*	-.04	.05	-.06
8. Unusualness							—	-.05	.34*	.04	-.04	-.13
Big Five												
9. Extraversion								—	.31+	.41*	-.06	-.12
10. Agreeableness									—	.24	-.08	-.05
11. Conscientiousness										—	-.28	-.43*
12. Neuroticism											—	.18
13. Openness												—

+$p < .1$, *$p < .05$, **$p < .01$, ***$p < .001$

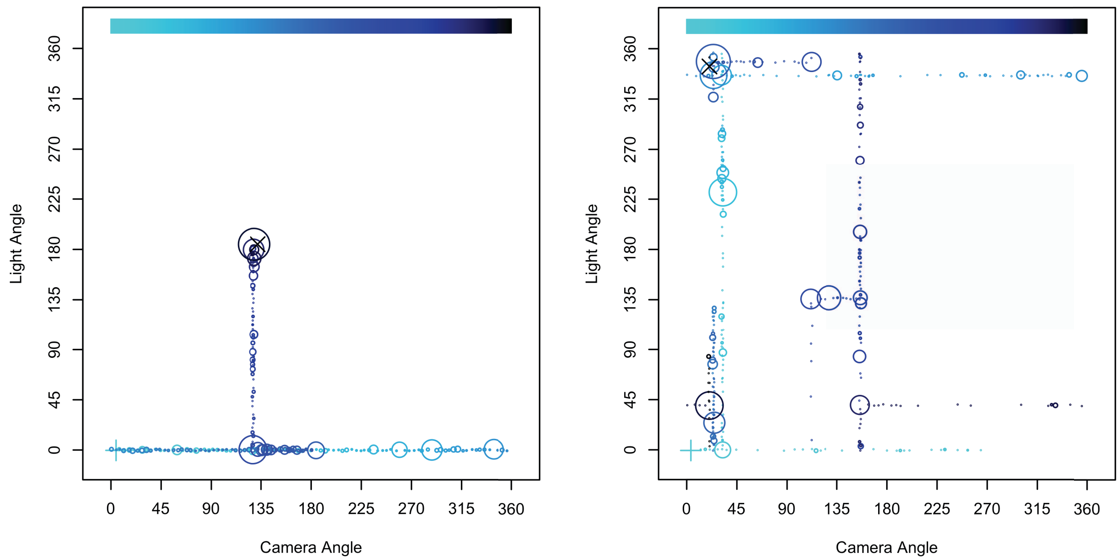
Table 2. Intercorrelations between metrics and personality.

of the problem itself. The intent in designing these scenes was to introduce problem complexity via the interplay between materials. However, people were free to choose what criteria they used, and if they did not notice or care about this interplay, their criteria may have been simpler.

For illustration, two sample trajectories are shown in Fig. 2. Each trajectory starts at the cross and ends at the X , with color indicating the passage of time (light blue to black). The size of the circle at each point is proportional to how long the person spent looking at that image. The participant on the left did not mention material properties when describing his/her criteria, while the participant on the right did.

To test whether criteria involving the interplay between materials was associated with more complex search trajectories, participants open-ended descriptions of their search process were coded for whether they mentioned material properties (e.g., re ection, refraction, transparency, and color). Comparisons were made between people who mentioned material properties ($N = 14$) and those who did not ($N = 20$). Statistically controlling for time, people who mentioned material properties made more dimension changes ($M = 1.77$ vs. $M = 2.96$, adjusted). No other e ects were signi cant.

Individual Differences There were some interesting individual di erences in search strategies. Most notably, the time spent searching was signi cantly and positively related to the trait agreeableness (a tendency to be compassionate and cooperative), basically suggesting that nice people took the experiment seriously. People who are more conscientious (self-disciplined, duty-bound, and achievement oriented) trended toward exploring more of the space, explored more diverse regions in the space, and made more dimension changes. Finally, people who are more neurotic (prone to stress and anxiety) showed more reversals in their search.



Time	Coverage	Fixations	Fix. Div.	Dim. Chgs.	Rate	Revs.	Unusual
1:45	1.67%	11	131	2	2.03	8	-.19
1:52	3.74%	32	127	9	3.37	19	.13

Fig. 2. Two sample search trajectories.

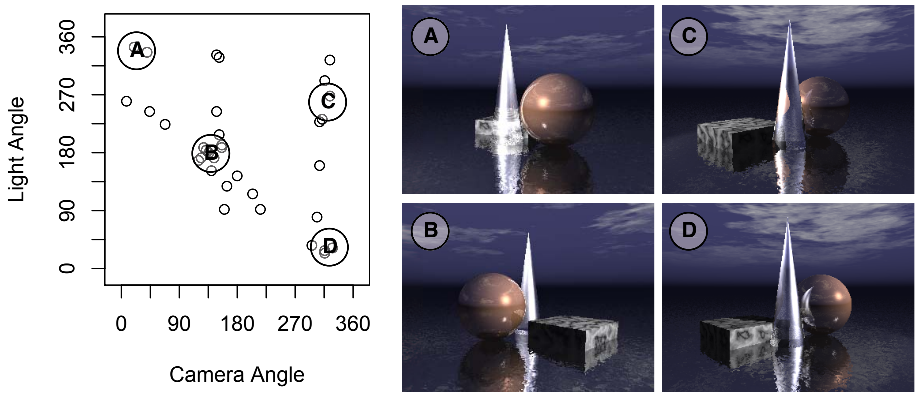


Fig. 3. Final points, with four examples.

Overall, these results show that search strategy is largely dependent upon how thoroughly the participant approached the task, which appeared to be higher for people who either nicer (agreeable) or careful and duty-bound (conscientious). Conscientious people in particular appeared to "leave no stone unturned", as evidenced by more dimension changes. Beyond this, more anxiety-prone (neurotic) people reversed their search direction more. All of these effects appear to be independent of the effect of criteria complexity, which was itself unrelated to personality.

Final Points Fig. 3 shows the final points for all 34 participants. As images B, C, and D illustrate, there was a strong preference for images where the three objects were composed evenly. (The apparent diagonal line does not correspond to any regular pattern when examined further.)

As shown in Table 2, the unusualness of the final point appears to be positively related to the rate of the search and the number of reversals, and to agreeableness. After controlling for rate or reversals, the effect for agreeableness is insignificant, suggesting that there may be a mediating effect. If replicable, this would suggest a mechanism by which agreeable people might reach more unusual points. The ability to detect mediating relationships between external variables (like personality or situational influences) and outcomes (like unusualness or creativity) via search trajectory characteristics is a strength of this approach.

Taken together, these early results show areas of promise and room for improvement. First, while some people did appear to notice the material properties, and while this did appear to have some influence on search strategies, the effect was not very large. In future experiments, the scene should be designed to make the material interplay more apparent. Second, while there were interesting relationships between search strategies and personality, the strong effect of agreeableness says more about the experimental setting than about the nature of the task itself. Future experiments should nd ways to encourage people to take the task more seriously without inducing undue demand characteristics. Third, while the metrics themselves have intuitive meanings, more work needs to be done to nd and understand the most relevant metrics for characterizing di erences between trajectories. Despite these problems, the initial experiment was able to nd meaningful relationships among variables and su cient inter-individual variability to suggest there is more to be found in future studies.

3 Discussion

This paper describes a new research technique for making detailed observations of the human creative process. While not as face valid as protocol analysis or holistic assessment, the technique is more economical and o ers more detailed information, making it well-suited for the aims of investigating how personality and situational in uences a ect the creative process, and for exploring connections between creativity and optimization. Preliminary results using the technique show that there are many di erences in how people approach the search task, some of which stem from personality variables, and some of which stem from what sorts of images people prefer.

Future Directions The next step in this research is to better understand the experimental task itself, which includes honing the user interface and experimental setting, re ning and better understanding the search trajectory metrics, and experimenting with scenes of varying complexity. From here, speci c questions can be explored that will add detail to current psychological knowledge about how various personality and situational in uences a ect creativity.

Beyond the exploration user interface, three additional user interfaces have been constructed. One interface selects representative points from the search trajectory, and asks participants to rate their interest in each image. Another interface plays the entire search trajectory back at low speed, allowing participants to provide a continuous rating of what they re seeing. The nal interface asks participants to rate the similarity of pairs of images from the space, which can be analyzed with multidimensional scaling. These tools are designed to reconstruct participants overall evaluations of representative points in the space, and to determine what evaluation dimensions participants use.

With these additional interfaces, the goal is to demonstrate that the scene being explored has two features: interdependencies, and local maxima. Interdependencies are desirable properties that con ict with each other (such as brightness diminishing re ections), in turn making the search less straightforward. Local maxima are points in the space that are better than similar points, but worse than very di erent points.

As stated at the outset, nding the best overall point is more di cult for problems that have interdependencies and local maxima. Metaheuristics are a class of non-deterministic algorithms for optimizing in such cases, and work by carefully tilting the balance from diversi cation (exploring many possibilities) toward intensi cation (pursuing a single local maximum) [2]. The exploration task should yield data suitable for detecting similar tendencies in human creators. By showing links between the nature of creativity and optimization as well as between how humans and computers approach each, this research will help expand the creativity as search metaphor.

While the aim of this technique is to be comprehensive yet economical, there is nothing preventing more complex applications. One such avenue would be to have participants think aloud as they search, which could then be analyzed and correlated with their search behavior. While time-consuming, this work could help determine things like whether and when people s criteria change mid-search, and how aware people are of their exploration strategies. This kind of work will be particularly useful for determining where creative search and optimization di er, and could even suggest new insights for authors of optimization algorithms, creative arti cial intelligence, or creativity simulations.

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