Chaos

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STRANGE BETA: An assistance system for indoor rock climbing route setting

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This paper applies the mathematics of chaos to the task of designing indoor rock-climbing routes. Chaotic variation has been used to great advantage on music and dance, but the challenges here are quite different, beginning with the representation. We present a formalized system for transcribing rock climbing problems and then describe a variation generator that is designed to support human route-setters in designing new and interesting climbing problems. This variation generator, termed STRANGE BETA, uses chaos to introduce novelty. We validated this approach with a large blinded study in a commercial climbing gym, in cooperation with experienced climbers and expert route setters. The results show that STRANGE BETA can help a human setter produce routes that are at least as good as, and in some cases better than, those produced in the traditional manner. © *2012 American Institute of Physics*. [http://dx.doi.org/10.1063/1.3693047]

In this paper, we describe a human assistance system whereby a computer guides a human user in a complex creative task: indoor rock climbing route setting. In 2003, approximately 3% of the U.S. population, or 8.7 million people, participated in some sort of rock climbing. Perhaps more importantly, the problem of route setting is representative of a large class of dynamic creative tasks and our work here presents a novel strategy for an assistance framework. We evaluate our proposal in a large blinded study in a commercial climbing gym and find that route setters are able to set routes preferred by climbers using our software. Although our application is specific, our approach is general, and we believe that this work serves as an important step in terms of understanding how computers can act as assistants in complex creative tasks.

I. INTRODUCTION

Computer assistance in creative tasks, generally the domain of cognitive science or artificial intelligence research, is a well-established idea that has attained some success over the past decades. For instance, pseudo-random sequences have been used to create music and art.[1–4] In this paper, we are concerned with the more modest goal of assisting humans in a creative task: in particular, using the mathematics of chaos to generate variations on indoor rock climbing routes. A similar approach has been successfully used for generating interesting variations in domains such as dance choreography and music composition.[5,6] In these applications, the hallmark "sensitive dependence on initial conditions" of chaotic attractors is exploited to generate a variation that deviates sufficiently from the input to be unique and interesting while maintaining its basic style. In this work, we adapt these techniques to the domain of indoor climbing routes and validate our approach via a large study in a commercial climbing gym. We show that computer-aided route setting can produce routes that climbers prefer to those set traditionally.

The key contributions of this work are as follows: (1) a language for the representation of climbing problems; (2) a chaotic variation generator that is designed specifically for climbing problems; (3) a user interface that allows human route setters to easily explore the space of possible variations and automatically generate easy-to-use route plans; (4) validation of the chaotic variations in a commercial climbing gym, using a robust research instrument, in cooperation with expert setters and experienced climbers; and (5) a publicly available implementation at strangebeta.com.

Section II provides a discussion of the most relevant related work. Section III introduces the problem domain and defines useful climbing-related concepts; Sec. IV gives an overview of how STRANGE BETA is used. Section V presents our language for describing climbing routes and discusses its strengths and limitations; Sec. VI reviews the mathematics of chaotic variation and our specific implementation of that strategy. Section VII describes the STRANGE BETA tool and its results. Section VIII describes the design, implementation, and analysis of our evaluation study at the Boulder Rock Club commercial climbing gym. In Sec. IX, we discuss future directions and conclusions.

II. RELATED WORK

As mentioned above, the use of computers in creative tasks—for independent generation and/or in assistance roles—is not a new idea. Computation has a particularly rich history in music composition, in both generative and assistant roles.[2] Route setting for indoor climbing is viewed by its practitioners as a creative task on par with music composition, requiring substantial expertise in order to create routes that are both of an appropriate difficulty and interesting to climb. A climbing route is a prescribed sequence of dynamic movements: a sequence of symbols from a complex language not unlike a dance or a tonal music composition, both of which can also be viewed as symbol sequences. All three of these domains—climbing, music, and dance—have strong

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notions of "style," but those notions are very hard to formalize, even for experienced practitioners.

The challenge in creating a variation on a sequence in any of these domains is to introduce novelty while maintaining stylistic consonance. The structure of a chaotic attractor can be exploited to accomplish this. Two projects that apply this idea to the realms of music composition and dance choreography are especially relevant to STRANGE BETA. Diana Dabby proposed the idea of exploiting the properties of chaos—the counterintuitive combination of the fixed structure of a chaotic attractor and the sensitivity of its trajectories to small changes—to generate variations on musical pieces.[6] In her work, a musical piece is codified as a sequence of n pitches (symbols). A "reference trajectory" of length n is generated from the Lorenz equations, starting at some initial condition (often (1, 1, 1), which is not actually on the attractor), and successive points on the trajectory are assigned to successive pitches in the musical piece. Next, a second trajectory is generated with a different initial condition—say (0.999, 1, 1). Dabby's variation generator steps through this new trajectory from start to end. It examines the x coordinate of the three-dimensional state-space vector at each point and then finds the point in the reference trajectory whose x value is closest to but not greater than that value. The pitch assigned to this point is then played. Variations generated in this fashion are different from the original piece and yet reminiscent of its style. This technique is fairly straightforward, but the selection of good initial conditions can be quite a challenge and that choice strongly affects the results.

Chaographer uses similar ideas to create variations on movement sequences, but with slightly different implementation of the mathematics and some necessary domain-specific changes.[5] In Chaographer, a symbol describes the state of 23 joints, which combine to articulate a body position. The nearest-neighbor calculation is generalized to the full dimension of the state space—without the directional restriction in Dabby's work—and care is taken that the initial condition falls on or near the attractor, which removes some of choice issues and their implications. The resulting movement sequence variations are essentially shuffled concatenations of subsequences of the original; the stylistic consonance derives from the subsequence structure, while the novelty derives from the chunking and shuffling. Chaographer's companion tool, MOTIONMIND, uses simple machine-learning strategies to smooth the potential dissonance that can occur at the subsequence boundaries.[7] MOTIONMIND uses transition graphs and Bayesian networks to capture the patterns in a corpus of human movement and then uses those data structures to find a series of movements that create stylistically consonant interpolations. In a simple Turing Test, the chaotic variations were found to be only marginally less aesthetically appealing to human judges than those created by human choreographers.[8]

III. ABOUT INDOOR CLIMBING

In this section, we give a brief overview of the mechanics of indoor climbing and climbing route setting. This discussion is extended in a companion technical report, complete with a glossary of terms.[9] Additional information can also be found in handbooks for route setters themselves, such as "The Art of Coursesetting" by Anderson.[10]

While once just for training, indoor climbing has become a popular sport of its own, with at least one and sometimes several dedicated climbing gyms in most major cities. A survey conducted by Roper Research for the Recreation Roundtable reported that in 2003 approximately 3% of the U.S. population,[11] or 8.7×10^6 people, participated in some sort of rock climbing.[12] In England, participation in climbing was one of the few sports that was on the rise in 2010.[13] Overall, the popularity of indoor climbing is likely to continue to increase substantially, especially as it has been short-listed for the 2020 Olympic Games and is being popularized by organizations focused on competitive climbing.[14,15]

Indoor climbing walls are designed to mimic rock formations. They are often textured and are covered with embedded "t-nuts" so that hand holds or foot pieces ("jibs") can be bolted to the surface in different configurations and orientations. T-nuts can be arranged on a geometric grid or in some approximation of a uniform random distribution. Holds—generally polyurethane, but sometimes made of wood, rock, or other materials—come in all shapes and sizes.

Climbers have an informal but fairly consistent language for describing holds, which involves a relatively small vocabulary of colloquial terms. The majority of handholds can be classified into large open upward-facing pockets ("jugs"), small edges ("crimps"), or convex rounded holds ("slopers"). There are also more esoteric shapes (e.g., "sidepulls" and "Gastons") and composite shapes. Despite the large number of possible shapes, climbers describe holds using a readily parseable domain-specific grammar that focuses on the holds' function, quality, and orientation.[9]

Holds are placed on the wall by experienced route setters to form a "problem" or a "route"—a series of holds with designated start and ending holds. Between those endpoints order is unspecified; part of the challenge for the climber is to find the right sequence of holds, which may not be at all obvious. Climbers use the word "beta" to refer to information about how to climb a given route. Routes differ in length; short ones that do not require a rope for protection are called "bouldering" problems. Longer routes that require mostly side-to-side movements are called "traverses." Since multiple problems coexist on a single wall—and can even share holds—route setters use colored tape to show which hold is part of which problem.

Difficulty is determined using a subjective scale. There are several scales in use; in this paper, we employ the widely used Yosemite Decimal System (YDS). YDS is a subjective consensus-based scale, where the easiest problems requiring a rope are given 5.0. There is no upper bound, with the currently "most difficult" climb rated 5.15. A postfixed minus or plus (e.g., 5.12-) indicates that the route is on the "easier end" or "harder end" of the grade. A more common convention is to use the letters a, b, c, and d (where a is easier and d is harder) to more precisely grade a route (e.g., 5.10b).

IV. STRANGE BETA: OVERVIEW

The rest of this paper describes the details of the design, implementation, and testing of STRANGE BETA. By way of context for that discussion, this section presents a prototypical scenario of its use by an experienced route setter. Such a setter might want STRANGE BETA's assistance for a host of reasons, foremost among which is creativity block (or simply looking for additional inspiration). We also imagine that such a tool could assist in the training of novice setters.

The first step is to transcribe one or more routes using the computer-readable language described in Sec. V. In doing this, the route setter can make use of routes from any domain (i.e., outdoors, indoors, bouldering) These routes, which will serve as input to the variation generator, are stored by the software in a route database. Routes transcribed by others can be used as well, but this is not without problems, as we discuss below. Variations generated by STRANGE BETA can themselves be used to generate other variations, or mixed with additional routes to inject other styles.

When a route-setter is ready to create a new problem, she chooses one or more routes from the database. In the simplest scenario, she picks a single route, but we have found that it is often more interesting to pick two or more routes to "mix." If the chosen routes are of a consistent grade and style, then the generated variation will be of a similar style and grade. Combining vastly different routes—either in terms of style or grade—can have unexpected, but often very interesting, results.

STRANGE BETA has a variety of controls, which set the values of the free parameters in the chaotic variation algorithm that it applies to the chosen routes. In our implementation, these are presented to the user in the form of presets ("default" values and "more variation" values). A setter who is experienced with the software can choose to vary the initial conditions or parameters of the algorithm in order to explore alternatives or fine tune the results.

The resulting variation is presented as a "route plan," i.e., a sequence of moves expressed in the language of Sec. V. To help the setter make sense of the new route, this route plan includes a set of annotations that describe how the variation differs from the original(s). The setter can print this plan and use it for direction while setting a route. During that process, the setter may choose to make improvisations or corrections to the variation.

V. ROUTE DESCRIPTION LANGUAGE

The first challenge in this project was to create a descriptive language for climbing problems that accurately captures the salient features of the domain, in sufficient detail to produce interesting variations, while not being so complex as to form a barrier to use. STRANGE BETA's language, which we call CRDL ("climbing route description language"), is designed to match the epistemology of this domain. An example CRDL description of a short problem is given in Figure 1.

In this formalization, we specifically model the sequence of the hand movements (L for left and R for right), but leave out the foot positions. This assumes that a route-setter could easily choose foothold placements that match the style of the upper-body movements and produce a route with the desired difficulty. Similarly, the wall's characteristics (e.g., steepness) are left out. As we show in Sec. VIII F, these assumptions are reasonable; the steepness is closely associated with difficulty and foot holds can fairly simply be placed to support desired hand movements.

It is worth noting that these design choices reflect a focus on the sequence of movements, rather than on the specific placements of holds on the wall. The effect of this is to encourage the person who performs the transcription of the route to record their subjective understanding of how the route should be climbed. This is exactly what climbers call "beta." This choice regarding the language design also means that in order to transcribe a route properly, the person doing the transcription needs to have a good grasp of the climb and may have climbed or set it herself. This, too, is implicit in climbers' use of the term "beta," and is supported by recent work showing the efficacy of pre-ascent visualization and planning by climbers.[16] CRDLS match to these understandings and conventions of the domain is intended to make STRANGE BETA easy for its target audience to use.

We evaluated the success of this language—and indirectly its accuracy and expressiveness—in two ways: interviews with users and the consistency of the results. We found that CRDL is a useful language for climbers and route setters. As compared to prior work, where individual joint orientations are modeled explicitly,[5,8] it is much more freeform and coarser-grained. As a result, setters found that it is

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Problem 13 from the CU–hosted RMR CCS
Climbing Competition in March, 2009.
A few large moves between moderate
crimps and slopers with thin/smeared
feet on a vertical wall. Set by Thomas Wong.
Intermediate Difficulty.
– – –
R slopey ledge
L match
R medium crimp sidepull
L diagonal sloper
R crimp (big move)
L sloper (bad) sidewaysish
R crack sidepull
L wide pinch
R match
```

FIG. 1. An example CRDL file of a route set by Thomas Wong for a climbing competition at the University of Colorado. All the text up until the line containing three hyphens is a header that describes the context of the route for posterity but is ignored (for now) by the variation generator.

not a chore to transcribe a climbing problem in CRDL, whereas the notions of specifying individual joint angles were incomprehensible to human choreographers. However, this flexibility comes at the cost of specificity—routes transcribed with this system might contain a fair amount of ambiguity.[17] Anderson suggests another language for describing routes in climbing competitions.[10] While similar to CRDL, Anderson's maps also document roughly where holds are placed in space relative to one another. Because of the complexity of implementing such a system, we have erred on the side of simplicity and omitted spatial information from CRDL. One could also impose more-stringent tests on this language, e.g., *If a given route A is transcribed by one person into CRDL, and that transcription T is used by another person to set a second route B, is it true that A is sufficiently similar to B that an experienced climber would recognize them as being subtle variations with the same underlying goals?* This is a matter for future work.

VI. GENERATING CHAOTIC VARIATIONS

To implement STRANGE BETA's chaotic variation generator, we follow the same basic design used in prior work.[5,6] Given a set of ordinary differential equations (ODEs), some reference initial condition IC_r, variation initial condition IC_v, and sequence of input symbols $i = \{i_1, i_2, ..., i_n\}$—the n moves in the "seed" route(s)—we use a fourth-order Runge-Kutta solver to generate two n-point trajectories in the state space of that ODE system: one called $\vec{r}$ beginning at IC_r and the other called $\vec{v}$ beginning at IC_v

$$\vec{r} = \{r_1, r_2, ..., r_n\}, \tag{1}$$

$$\vec{v} = \{v_1, v_2, ..., v_n\}. \tag{2}$$

We then create the mapping that associates the sequence of input symbols to the sequence of points in the chaotic reference trajectory ($i_1 \rightarrow r_1$ and so on). Finally, we step through the variation trajectory point by point, using a nearest neighbor algorithm (NNA) to find the nearest point in $\vec{r}$ for each v_k and, then output the sequence of associated symbols $o = \{o_1, o_2, ..., o_n\}$

$$o_j = i_k, s.t. k = argmin_l\{d(v_l, r_j)\}, \tag{3}$$

where $d(x, y)$ is some function that calculates the distance between two points x and y. This algorithm is equivalent to the approach used by Choreographer.[5] In Dabby's work,[6] however, the NNA is unidimensional and directional: it will find the nearest neighbor in the x-axis only if the neighbor is greater than or equal to the target. This causes the algorithm to find no neighbor for some inputs; it also disturbs the continuity of the variation because its projection can destroy neighbor relationships. Dabby suggests that in this case the user should "fill in the blanks."[6] Although we implement both versions of the algorithm, our preference is for a strict Euclidean NNA of the sort presented in Eq. (3).

The choice of the ODE system and the initial conditions are critical to STRANGE BETA's success, as are the parameters of the solver algorithm. As in prior work,[5,6] we use the Lorenz system

$$\begin{aligned} x' &= a(y - x), \\ y' &= x(r - z) - y, \\ z' &= xy - bz, \end{aligned} \tag{4}$$

with $a = 16$, $r = 45$, and $b = 4$, arguably the canonical example of a chaotic system. We used a solver step size $h = 0.015$. We chose a reference initial condition near the attractor: $IC_r = (-13, -12, 52)$. An example trajectory $\vec{r}$ from this initial condition is shown in Figure 2, together with one of the variations $\vec{v}$ that we explored in this project.

Dabby investigated other ODE systems but found the Lorenz equations to be the most desirable.[6] Similarly, we considered a Rössler attractor but were unable to convince ourselves that it generated more-interesting variations—especially given the short lengths of our trajectories, which are typically on the order of 30 symbols. In short, while there may be some value in using other systems, the Lorenz system is sufficient for our purposes and has the benefit of allowing a more direct comparison to prior work in other domains.

The choice of symbols is, as alluded to above, another key to the success of this strategy. We treated each move—i.e., each line in a CRDL input sequence like Figure 1—as an individual symbol. It is not clear whether it makes more sense to vary the left and right hands separately or together. Here, we varied them together; we will explore the other approach in future work.

STRANGE BETA shares some of the challenges faced by previous chaotic variation generators. Route-setters, like musicians or dancers, are not necessarily familiar with computer-readable formats, ODE solvers, and chaotic dynamics, so the user interface requires some real thought. The software is web-based; its output is a "Chaotic Route Plan" that reproduces the input route(s) alongside the variation. It specifically indicates which moves in the variation have been changed and identifies their provenance (i.e., which input sequence they came from and where). Figure 3 shows a screenshot made during the process of generating a variation on two input routes.

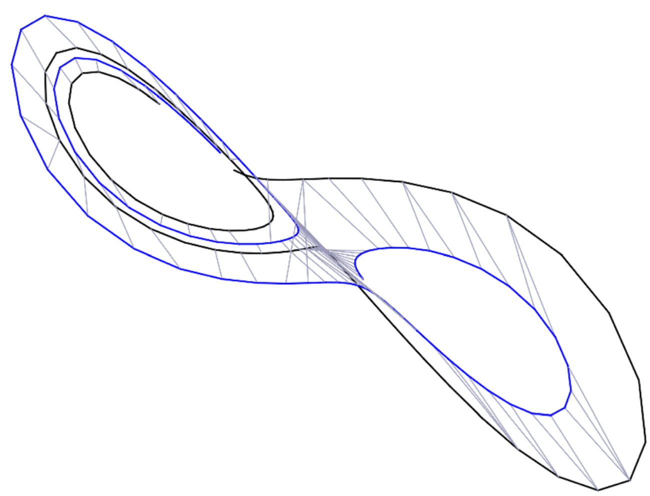

FIG. 2. (Color online) Reference (black) and variation (blue/gray) trajectories for $IC_r(-13, -12, 52)$ (black), $IC_v = (-16, -13.5, 52)$ (light blue) projected on the X-Z plane. The gray lines show the associations between reference and variation points that produce the corresponding variation sequence.

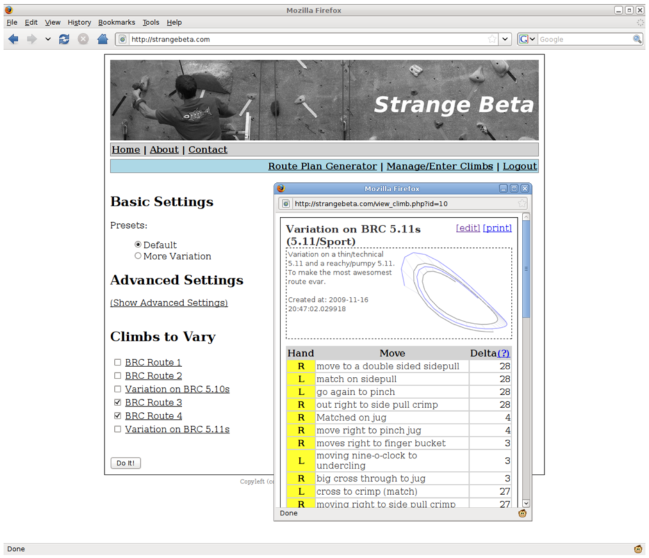

FIG. 3. (Color online) Screenshot of STRANGE BETA software being used to generate a variation on two input routes.

The centerpiece of this figure is the chaotic route plan: the varied sequence together with the annotations about changes and provenance, a picture of the corresponding trajectories, and some details about how they were generated. This route plan can be printed and used by the route setter, as described in Sec. IV.

Another challenge that STRANGE BETA shares with previous approaches to chaotic variation is novelty. In both Chaographer and Dabby's work,[5,6] the varied trajectory can only contain a re-ordering of the specific set of unique symbols in the reference trajectory. Given the large language of possible climbing movements, this is an unnatural restriction. As one solution, we suggest the use of simple machine-learning techniques to bring "new" or "unique" movements into a variation trajectory, as was done in MOTIONMIND.[7,9] This is discussed at more length in Ref. 9.

Climbing routes pose some new challenges for chaotic variations as well:

1. There are dependencies between some movements. The most obvious example is a "match," where a climber places both hands on the same hold simultaneously. In a match move, two seemingly independent movements actually only involve one hold. How should these dependencies be enforced without reducing the chances for interesting variation?
2. Dances and sonatas contain hundreds or thousands of notes and movements, but climbing routes are much shorter. What are the implications of this? How do we generate an interesting variation on a three- or five-move problem?

To address the first issue, we simply replace match moves with the previous movement of the other hand and add a note to the route plan: "(match?)" This is intended to let the setter know that this move was used as a match move in the input problem. We address the second issue by using multiple climbs as input. This has the effect of both increasing the trajectory length and incorporating more movement types. When doing this, we generally try to include routes that are both stylistically similar and of a compatible difficulty. The result is a variation that takes cues from both routes and is longer than both. In the scenario where radically different routes are mixed, the result can be unpredictable. For instance, if a setter chose to combine an "easy" route (e.g., 5.4) with a very difficult route (e.g., 5.13), the resulting variation is unlikely to be a successful climb, involving sections of intense difficulty and complexity surrounded by straightforward movement requiring little effort (by an experienced climber). Over-long variations are not a problem; the setter can simply select a chunk of the variation or eliminate uninteresting sections.

VII. SPELUNKING FOR INITIAL CONDITIONS

With an effective chaotic variation generation algorithm in hand, our next challenge is to help the user choose an IC_v that creates a variation that is sufficiently different from the input while also preserving the style. To this end, STRANGE BETA takes a brute-force analysis approach. Given some IC_r, we place points on a $N \times N \times N$ point grid around it, spaced evenly on intervals of size s. N and s are free parameters of the algorithm; generally, $N = 100$ and $s = 0.01$ provide a sufficiently complex picture of the IC landscape, and so are set as the defaults. Experienced users can change these values if they wish.

To help users make sense of this space of possibilities, STRANGE BETA color-codes points in that space according to the characteristics of the variation. Specifically, we calculate two measures of difference between the reference trajectory and the variation trajectory: *effect* and *change*. Effect is the number of symbols that would be changed in a chaotic variation. Change is the average distance (in terms of index) that those changed symbols would be moved. Figure 4 plots these two metrics for a specific instance.

The effect runs the gamut from no change (the red region) to having every move changed (the purple region). However, at those same points, the change metric tells a different story; instances are visible where every move is changed, but only by a small amount (purple effect, red change). The opposite situation also arises, where a small number of moves are repositioned far from their original position in the route. In addition to these extremes, there are examples of just about every condition in between.

Effect and change plots vary significantly for different parameter values. We generated similar plots for different s values, different NNAs, and in different projections (clearly we must project because these metrics are four-dimensional). Each combination generates pictures with different geometry, but the patterns in Figure 4 are generic and representative, so we chose this IC_r value as the default setting for STRANGE BETA, along with the $IC_v = (-16, -12, 52)$ that is drawn left of center in Figure 4 and the 2-dimensional Euclidean NNA calculation.

To help users sift through these results and explore different IC_vs, we implemented an "IC picker" tool that preprocesses the data and finds candidate ICs, given a desired amount of change or effect. This automates the otherwise onerous process of varying parameter values and examining

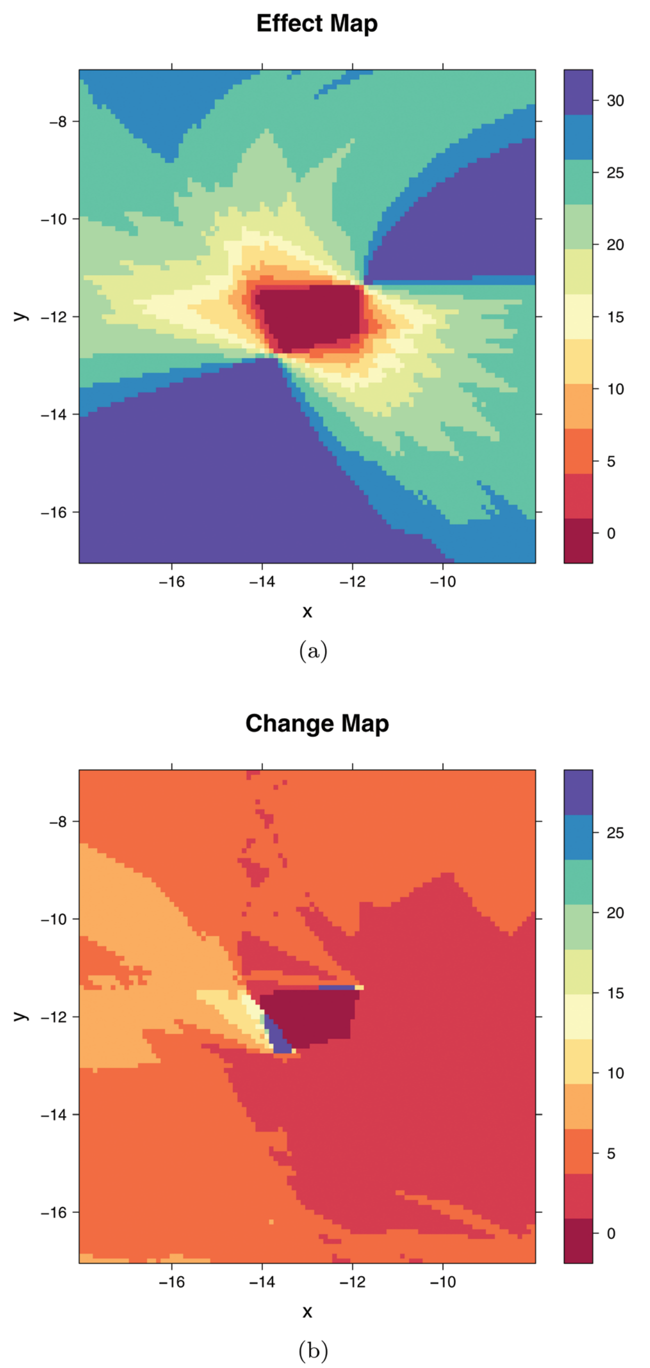

FIG. 4. (Color) Effect and change for $IC_r = (-13, -12, 52)$, $N = 100$, $s = 0.1$ in the x-y plane (i.e., with z held constant at 52) using 2D Euclidean distance for nearest-neighbor calculation. In both maps, "cold" colors (e.g., blue and purple) indicate the largest amount of variation (effect or change) and "hot" colors indicate little or no change. Using this color map, neutral or average change is colored yellow.

dozens of plots in order to find appropriate values for one's needs. This tool also makes it easy to find multiple—possibly disparate—conditions with similar change and effect characteristics.

Generating plots like this requires a great deal of computation and produces a substantial amount of data—$N = 100$ results in 1 000 000 unique ICs and as many runs of an ODE solver on Eq. (4), for instance. Thankfully, this problem is easily parallelizable. To compute the results in a tractable amount of time (30 min versus 2 days), we made use of a 16 node, 128 CPU cluster, with each of 100 nodes processing 10 000 trajectories. Although this is a tremendous amount of computation, it must only be performed once for each set of parameters and can be calculated offline. The resulting static map is then included with STRANGE BETA so that a user can fine-tune the amount and style of blending by selecting different ICs from the map.

VIII. EXPERIMENT AND ANALYSIS

To analyze the effectiveness of the system as a whole, we carried out an experiment at a large climbing gym, the Boulder Rock Club (BRC), in collaboration with two expert setters, Tony Yao (T) and Jonathan Siegrist (J), and the editors of *Climbing* magazine.

A. Experimental design

After consultation with these experts and the other setters at the BRC, we decided to set four routes, two at a grade of 5.10 and two at a grade of 5.11. One route of each grade was set using our chaotic method and the other two were set traditionally. Using a questionnaire, we measured the attitude of climbers towards the four routes. Again, this study was blind: climbers were not aware of the research question. As input to the variation generator, we chose four existing routes in the gym, two of each grade, both well regarded. All four routes were transcribed by T. The two variations were generated by author CP, using STRANGE BETA with $IC_v = (-16, -13.5, 52)$ and $IC_r = (-13, -12, 52)$. We chose to skip the first 100 integrated points of the trajectory to further avoid transient behavior. Each route involved approximately 30 holds on an approximately vertical 10.7 m wall of the same steepness. We chose to place the routes on near-vertical walls of the same steepness to avoid any confounding effects in rating due to the steepness of the climbs. Indeed, steeper climbs have been shown to require greater physiological output at the same difficulty.[18]

On 30 September 2009, T and J set the four routes using the resulting chaotic route plans. Afterward, we interviewed them to record their thoughts on the experience, which we have summarized below. Questionnaires were made available at the front desk of the climbing gym for willing participants and fliers were posted throughout the gym to advertise the opportunity to participate. Incentives for participation were provided by *Climbing* magazine. All participants provided ratings for each of the four climbs, presumably in the same climbing session.

Over the course of approximately 2 weeks, 44 (presumably unique) climbers completed questionnaires with mean ability, in terms of typical upper-end outdoor climbing grade, of 5.11c. Minimum ability was 5.10; maximum was 5.12d. Draper *et al.* have shown that climbers generally provide accurate self-assessments, hence we believe these responses are likely honest and objective assessments of their climbing ability.[19] On average, participants reported that they climb indoors between two and three times per week and had been climbing 12 yr, with a minimum of 6 months and maximum of 53 yr. Although we believe this sample to be fairly

TABLE I. The BRC study instrument: a 14-item Likert scale intended to assess participants' attitude towards a given climb. Cronbach's α is a measure of internal consistency; τ is a measure of correlation, which is being used as a secondary measure of consistency, and questions that are negatively keyed (i.e., a positive response indicates a negative attitude) are flagged.

Number	Question	τ	α	Negative response
1	Too easy for the grade	−0.108	0.750	X
2	Too difficult for the grade	0.184	0.703	X
3	Difficulty is consistent throughout the climb	0.220	0.696	
4	Requires thoughtful/nontrivial beta	0.117	0.707	
5	Has good flow throughout	0.536	0.661	
6	Appears to be well thought out	0.556	0.650	
7	Is creative/has interesting moves	0.480	0.657	
8	Climbs awkwardly	0.413	0.668	X
9	Good variety of handholds/types of grips	0.161	0.705	
10	Has a definite crux	−0.121	0.753	
11	Crux is technically engaging	0.043	0.719	
12	Has an unpleasant/stopper crux	0.173	0.701	X
13	Is a route I would climb again	0.560	0.645	
14	Is a route I would recommend to others	0.633	0.638	

unbiased and representative of the population of indoor climbers as a whole, we cannot claim that this sample is random and hence our analysis is constrained to making conclusions about the preferences of these 44 participants with regard to the specific four climbs we set.

B. Survey instrument

The questionnaire that we designed to interpret climbers' reactions and preferences about these routes used standard, well-accepted techniques for construction of attitude surveys.[20–22] In summary, participants were asked to rate each climb using a 14-item five-point summative Likert scale. The five-point response format used the standard response categories (Strongly Agree, Agree, Neither Agree Nor Disagree, Disagree, and Strongly Disagree), to which we have assigned ordinal values of (2, 1, 0, −1, −2), respectively.

Table I lists the Likert scale questions used to evaluate each route along with their internal consistency metrics. The α value should be considered relative to the overall α of 0.708. τ is the Kendall's τ correlation coefficient for each question's rating, as correlated with the overall rating. Hence, a question with a large τ and large α relative to the mean is generally consistent with the overall results.[20] Some questions are negatively keyed to avoid bias from having all questions be repetitively positive or negative. For instance, question 1 asks whether the route is too easy for the grade (a negative statement) and question 5 asks whether the route has good flow (a positive statement). In addition to the Likert scale, this questionnaire requested some domain-specific demographic information and asked participants to rank-order the climbs (which served as an external consistency check) and list the order in which they climbed them (which served to expose any ordering bias). These questions are listed in Table II.

Internal consistency analysis showed that items 1, 9, 10, and 11 produced the greatest inconsistency and were eliminated from analysis, resulting in a 10-item summative scale with an overall Cronbach $\alpha = 0.834$ (versus 0.708 before censoring). This value indicates that the research instrument is strongly consistent.[23,24] In addition to the Likert scale, climbers were asked to provide the order in which they climbed the routes. Some recent work has shown that a climber's experience on a route may be affected by whether they lead-climb or top-rope a route, and whether they have visually inspected it before climbing it.[16,25] In this survey, we did not ask the climbers to specify whether they completed each climb without falls, or whether they practiced or studied the route visually before climbing it. In future work, we plan to include these questions in our survey.

C. Climb preference

Interpreting the summed Likert scale data as ordinal, we can compute the median values for the four climbs, which are given in Table III. Applying a Wilcoxon rank-sum test to the 5.10 climb's scale data, we were unable to reject the null hypothesis that the medians are equal (p-value $= 0.54$). In the case of the 5.11 climbs, however, we were able to reject this null hypothesis: for this sample, the difference between medians is significant (p-value $\ll 0.05$). In other words, we

TABLE II. Demographics and other questions from the BRC study. Climber ability, experience, and order were used to assess possible correlations with climb preference. Climb ranking was used as an external consistency metric. To the disappointment of the authors, no significant correlation was found between ice cream preference and climber ability.

Question
Years climbing?
Years climbing in a gym?
Hardest indoor redpoint?
Hardest outdoor redpoint?
Days per week climbing outside?
Days per week climbing at the BRC?
Typical indoor grade range?
Typical outdoor grade range?
In what order did you climb the routes (e.g., 1, 4, 3, 2)?
What is your overall ranking of the routes from best to worst (e.g., 4, 2, 1, 3)?
What is your favorite ice cream flavor?

TABLE III. Results of BRC experiment. MSV is the median summed value, APRP is the average positive response percentage, and MR is the median rank.

Climb	Setter	Grade	MSV	APRP	MR	Chaotic
1	J	5.10	6	27.44	3	
2	J	5.10	4	25.58	3	X
3	T	5.11	9	37.23	1	X
4	T	5.11	4	26.21	3	

can state with confidence that climb 3 is preferred by this sample over climb 4, but we cannot make a similar claim about the 5.10 climbs, about which the participants were more indecisive.[26]

Because interpreting summative Likert scale data as ordinal may be viewed dimly by some conservative statisticians,[27,28] we also carried out a similar analysis using a convincingly continuous variable: percentage of positive (viz., Agree or Strongly Agree) responses to scale items—an approach common to marketing research, for example. Mean values for this variable are given in Table III. A Welch 2-sample t-test on these data produced congruent conclusions to those described earlier in this paragraph: we were unable to reject the null hypothesis that the 5.10 climbs have equal means, but we were able to reject this null hypothesis with high confidence in the case of the 5.11 climbs.

As a final indicator of climb preference, we asked participants to rank-order the four climbs. The median ranks (where smaller is better) are listed in Table III. We computed the inter-grade coefficient of concordance of these ranks using Kendall's method and found values of $W = 0.01$ with a p-value of 0.59 for the 5.10 climbs and $W = 0.38$ with p-value $\ll 0.01$ for the 5.11 climbs. These values further serve to indicate that raters are in agreement on their preference for climb 3 over climb 4, but are not clearly decided between climbs 1 and 2, and that the climbers preferred climb 3 overall.

D. Possible correlating factors

In addition to determining climb preference, we also made use of correlation tests to answer a pair of secondary research questions: (a) Is preference affected by climb order (i.e., do participants rate climbs differently when they are tired)? (b) Is preference affected by climber ability (i.e., do better or worse climbers rate climbs differently)?

To address the first question, we used Kendall's τ on the ordinal variable and Pearson's r on the continuous variable. These results suggested a correlation that is very near zero, both with high p-values. From this we concluded that there was no obvious correlation between climb order and climb preference—or, more precisely, that we cannot reject the null hypothesis that they are uncorrelated. We confirmed this conclusion using the pure ranking data, which also produced a Kendall coefficient near zero and a large p-value (near 0.95). We used the same tests to answer the second question, producing correlation coefficients (on the order of 0.1) with p-values greater than $\alpha = 0.05$, indicating that there is no clear correlation in the data between climber ability and climb preference.

These two questions correspond to the most obvious sources of data skew in our specific population. The τ and r results indicate that these concerns are unfounded.

E. Results summary

It is clear that the participants of the survey preferred climb 3, which was set with the assistance of STRANGE BETA, over climb 4, a climb set without it. In the case of the 5.10 climbs, participants may have preferred the climb set without the software, but not by a significant margin. It is worth noting that the four climbs that were used as input to the variation generator were transcribed by T. From this, one could conjecture that the software performs best when used by the same setter as did the original transcription. Although more work would be needed to confirm or deny this, we suspect that a flexible description format like the one we have chosen may allow setters to use personal idioms in their descriptions, preventing portability and reducing the effectiveness when these same descriptions are used by third parties. *In sum, we feel confident in making the claim that when used properly, in a scenario where an expert setter feels the use is appropriate, our software can assist in producing a route which is at least as well regarded as those routes produced without it. And, in some cases—indeed, in this study—STRANGE BETA can produce routes that are considered superior by climbers to those set purely by human experts.*

F. The setters' experience

The preferences of the climbers are only part of the assessment of STRANGE BETA; analyzing the opinions of the route-setters is also crucial to understanding the effectiveness of the system. To this end, we interviewed the setters after they had finished setting the four routes. The interview was conducted in a free-form fashion, simply asking the setters to provide feedback on their experience using the variations, whether they would be willing to use the software in the future, and whether they had any suggestions for how to make it more usable.

Although positive about the experience in general, both setters were hesitant to endorse anything that would lessen their creative control. Interestingly, this response is similar to that of composers,[6] but at odds with the more-supportive response dancers had to a similar experiment.[8] One of the two setters, J, found using the generated route plan to be unwieldy and time-consuming. This may, again, be a result of having the other setter, T, transcribe all four input routes, or it may be a user-interface design issue. During the course of the experiment, we identified several ways to improve the route-plan format and route-transcription process in order to attend to problems that both setters encountered using the system. Both setters, for example, found some aspects of the output format to be confusing (principally the inclusion of the input data). We have since removed this feature from the output.

To address our initial assumptions about the design of the route description language, we asked the setters whether it was reasonable for variations to leave the placement of foot pieces and the distance between holds, to their discretion.

They agreed that this was a reasonable assumption, as usually foot pieces are placed to accommodate hand movements. In general, the setters found the flexibility of the format to be beneficial and allowed them more creative control overall.

IX. CONCLUSIONS AND FUTURE WORK

In this paper, we have applied chaotic variations to a new domain with some unique and interesting challenges: indoor climbing route setting. We have proposed new ways of exploring the space of possible variations and validated the results in a user study. We found that our chaotic variation strategy is a useful assistant to human experts, helping them produce routes that are at least as well regarded as those set traditionally.

Though STRANGE BETA's chaotic variation facilities have been fairly well vetted, we believe there is substantial opportunity to extend this system with machine-learning, which we have begun prototyping and testing using data collected from the public implementation of STRANGE BETA.[9] In particular, we see great promise in the application of generative machine learning models, such as Variable Order Markov Models (VOMMs), to insert moves between reordered sequences, and "smooth out" unpleasant transitions. Beyond this, we believe there are particularly interesting opportunities for future work concerning representations, methodologies, and incorporation of additional domain knowledge. A formal evaluation of the symbol sets and the parser framework of which they are targets could lead to a more effective knowledge-representation framework, which would in turn support better models. Assessing how well STRANGE BETA works in different environments and for a large number of different setters will require a much more substantial experimental evaluation than we have done here.

Finally—and of most interest to us—is the incorporation of domain knowledge into STRANGE BETA's mathematics and models. Identification of the crux, the most difficult section of a route, is of particular importance. We know from our surveys that the quality of a crux is important to a climber's impression of the route. If we could identify the crux of a route, then we could determine whether or not a chaotic variation has one—and if it is of a reasonable size, shape, and position in the overall route. Ultimately, we would like to explicitly address the question of how human setters create interesting short sequences and use that understanding as a basis for a machine-learning solution. Existing research on biomechanical models for equilibrium acquisition while climbing[29] could support this endeavor, as it offers explicit models for climbing-related movement in route generation. These explicit mechanical models might be expanded with cognitive models for how climbers visualize climbs—a combination of not just movements but also specific application of force and effort.[30]

Gathering the data to support all of these research threads will require the continued interest and participation of the climbing community. To this end, we continue to prototype new features on the publicly facing implementation of the system at strangebeta.com. These data, and the associated results, would also contribute to existing academic research on rock climbing. Research on the exercise physiology of difficult climbing, for instance, has produced well-defined training guidelines for climbers.[31,32] STRANGE BETA could dovetail nicely with this, generating route variations aimed at specific training goals.

Overall, we believe that chaotic variations provide great promise in the realm of creative processes. Though there are many open questions and much to be done, the work described here serves two important purposes from the standpoint of the climbing community. First, it is a large step forward in terms of creating a functional prototype of such a system. And second, and perhaps most importantly, it has convinced us and others that chaotic variation is a useful technique in this domain. We are uncertain whether our approach to route setting will be widely adopted, in large part because expert setters enjoy the creative challenges of setting unique and interesting problems from scratch. However, we see promising applications when creativity block strikes or when teaching novice setters.

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[1] A. Bauer, "Random art," http://www.random-art.org/ (December 2009)
[2] J. Hartley, Leonardo **28**, 221 (1995).
[3] R. R. Shearer, Leonardo **25**, 143 (1992).
[4] J. Briggs, *Fractals: The Patterns of Chaos* (Touchstone, Simon & Schuster, New York, 1992).
[5] E. Bradley and J. Stuart, Chaos **8**, 800 (1998).
[6] D. S. Dabby, Chaos **6**, 95 (1996).
[7] J. Stuart and E. Bradley, in *Proceedings of the International Conference on Machine Learning (ICML)* (Omnipress, Madison, WI, 1998), pp. 547–555.
[8] E. Bradley, D. Capps, J. Luftig, and J. M. Stuart, Open Artif. Intell. J. **4**, 1 (2011).
[9] C. Phillips, L. Becker, and E. Bradley, "Strange Beta: An assistance system for indoor rock climbing route setting using chaotic variations and machine learning," Technical Report No. CU-CS-1087-11 (University of Colorado, Boulder, 2011).
[10] L. Anderson, *The Art of Coursesetting* (Wolverine, Silt, CO, 2004).
[11] According to U.S. Census data, the U.S. Population was 290 210 914 in July, 2003.
[12] Roper Research, "Outdoor recreation in America," Technical Report (The Roper Center for Public Opinion Research, 2003).
[13] S. England, "Active people survey 5," Technical Report, 2010.
[14] I. Mountaineering and C. Federation, "Uiaa," http://www.theuiaa.org/ (January 2011).

[15]International Federation of Sport Climbing, "International federation of sport climbing," http://www.ifsc-climbing.org/ (January 2011).
[16]X. Sanchez, P. Lambert, G. Jones, and D. Llewellyn, Scand. J. Med. Sci. Sports **22**, 67 (2012).
[17]Students of classical dance notation may notice a similarity to Beauchamp-Feuillet notation, which purposely omits details under the assumption that a trained dancer would know them intuitively.
[18]B. de Geus, S. V. O'Driscoll, and R. Meeusen, Eur. J. Appl. Physiol. **98**, 489 (2006).
[19]N. Draper, T. Dickson, G. Blackwell, S. Fryer, S. Priestly, D. Winter, and G. Ellis, J. Sports Sci. **29**, 851 (2011).
[20]A. Oppenheim, *Questionnaire Design and Attitude Measurement* (Basic Books Inc., New York, 1966).
[21]J. Green and J. Brown, *Principles of Social Research* (Open University Press, 2005).
[22]J. Bethlehem, *Applied Survey Methods: A Statistical Perspective* (Wiley, New York, 2009).
[23]J. A. Gleim and R. R. Gleim, in 2003 Midwest Research to Practice Conference in Adult, Continuing, and Community Education, 2003.
[24]D. L. Streiner, J. Pers. Assess. **80**, 99 (2003).
[25]N. Draper, G. A. Jones, S. Fryer, C. I. Hodgson, and G. Blackwell, Eur. J. Sport Sci. **10**, 13 (2010).
[26]It is worth noting that the setter of the 5.10 climbs, J, was displeased with his "chaotic" route and felt that STRANGE BETA had "helped" him produce a route that was below the standards he typically holds himself to (in fact, he was hesitant to sign his name to it). It is interesting to note that, while individual climbers may have preferred one route or another, they were generally ambivalent about the two 5.10 routes. One possible hypothesis, proposed by the setters with whom we worked, is that climbers are less decisive about the quality of less difficult routes.
[27]S. Jamieson, Med. Educ. **38**, 1212 (2004).
[28]J. Carifio and R. J. Perla, J. Soc. Sci. **3**, 106 (2007).
[29]F. Quaine and L. Martin, Gait and Posture **10**, 233 (1999).
[30]M. M. Smyth and A. Waller, Appl. Cognit. Psychol. **12**, 145 (1998).
[31]P. B. Watts, Eur. J. Appl. Physiol. **91**, 361 (2004).
[32]N. Draper and C. Hodgson, *Adventure Sport Physiology* (Wiley-Blackwell, New York, 2008).