Strange Beta: Chaotic Variations for Indoor Rock Climbing Route Setting

Caleb Phillips and Elizabeth Bradley

Abstract In this paper we apply chaotic systems to the task of sequence variation for the purpose of aiding humans in setting indoor rock climbing routes. This work expands on prior work where similar variations were used to assist in dance choreography and music composition. We present a formalization for transcription of rock climbing problems and a variation generator that is tuned for this domain and addresses some confounding problems, including a new approach to automatic selection of initial conditions. We analyze our system with a large blinded study in a commercial climbing gym in cooperation with experienced climbers and expert route setters. Our results show that our system is capable of assisting a human setter in producing routes that are at least as good as, and in some cases better than, those produced traditionally.

1 Introduction

Computer assistance in creative tasks, generally the domain of cognitive science or artificial intelligence research, is a well established idea that can claim varied success. For instance, there has been some success in utilizing chaotic dynamics or pseudo-random sequences to create art or music [4, 10]. In this paper, we are concerned with the more modest goal of using computers to *assist* humans in a creative task, particularly using chaotic systems to generate variations on indoor rock climbing routes. In prior work, chaotic systems have been successfully used for generating interesting variations in domains such as dance choreography and music composition [1, 3]. In these applications, the sensitive dependency on initial conditions of chaotic systems is exploited to generate a variation that sufficiently deviates from the input to be unique and interesting, while at the same time maintaining its basic style. In this work, we adapt these techniques to the domain of indoor climbing route setting and validate our approach via a large study in a commercial climbing gym. *We show that computer-aided route setting can produce routes what climbers prefer to those set traditionally.*

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 a city of sufficient size. A survey conducted by Roper Research for the Recreation Roundtable reported that in 2003, approximately 3% of the US population[1], or 8.7 million people, participated in some sort of rock climbing [9]. Indoor climbing walls are installed in configurations and orientations to mimic rock formations. Experienced route setters bolt polyurathane “holds” to the wall to form a “problem”. Holds come in all shapes and sizes; the most common hold shapes are jugs (large open steep-walled pockets), crimps (shallow ledges), pockets (open holes), and jibs (small foot pieces). Although there are also an infinite number of possible composite shapes that can form holds. Routes can be short (“bouldering”) or long and can be vertical or horizontal (“traverses”).

Department of Computer Science
University of Colorado, Boulder
caleb.phillips@colorado.edu, lizb@cs.colorado.edu

[1] According to US Census data, the US Population was 290,210,914 in July, 2003.

In the use case that motivates our work, we imagine a route setter who decides to seek assistance from our software while setting a route. She might choose to do this either because of a need for inspiration (creativity block), or perhaps because she is a novice setter in need of guidance. The first step involves transcribing several routes using the notation we describe in section 2 that can be used as input to the variation generator. These routes are entered into our software and stored in a route database. To generate a variation, the setter selects one or more routes to vary. The program presents the resulting variation, which can be printed and used directly while setting a route. The setter can deviate from the instructions as she sees fit, or choose to generate a different variation with new parameters, perhaps combining other routes or variations.

There has been some academic research on rock climbing in other fields that, while tangential, is largely supportive of our underlying goal to understand the mechanics and aesthetics of rock climbing. Substantial work in the exercise physiology of difficult climbing has produced well defined training guidelines for climbers that might be used to generate route variations aimed at specific training goals [13]. Although largely preliminary, there has been some effort to build biomechanical models for equilibrium acquisition while climbing [8]. If expanded, this work may offer a chance to better model the specific dynamics of climbing movements and thereby make use of explicit models for climbing-related movement in route generation. Alternately, 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 [11].

2 Route Description Language

The first challenge we face is to come up with a descriptive language for climbing problems that captures sufficient detail to produce interesting variations and properly distill the important features of a route while not being so difficult to use as to form a barrier to use.

In our proposed formalization, we specifically model the sequence of the hand movements (L for left and R for right), but leave out the feet positions, assuming 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 (i.e., steepness) are left out. Interviews with experienced routesetters have convinced us that these assumptions are reasonable, since the steepness is closely associated with difficulty, and foot holds can fairly simply be placed to support desired hand movements [7].

This language certainly succeeds in the goal of being flexible. As compared to the work in [1], where individual joint orientations are modeled explicitly, it appears exceptionally free-form. As a result, it is not a chore to transcribe a problem. However, this flexibility comes at the cost of specificity—routes transcribed with this system might contain a fair amount of ambiguity. Generally, we would like to think that our formalization is successful if it can pass an acid-test: *If a given route A is transcribed by one person, 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 on the same premise?* Whether or not our route description language passes this test is an open question.

3 Generating Chaotic Variations

To implement our chaotic variation generator, we followed the same basic design used in [3] and [1]. Given some reference initial condition IC_r, variation initial condition IC_v, and sequence of input symbols $i = \{i_1, i_2, ..., i_n\}$ we generate a chaotic trajectory for each IC of length n using a fourth order Runge-Kutta numerical integrator with step size $h = 0.015$:

$$r = \{r_1, r_2, ..., r_n\}, v = \{v_1, v_2, ..., v_n\} \tag{1}$$

We assign each input symbol to a point in the reference trajectory and then use a Nearest Neighbor Algorithm (NNA) on the variation trajectory, to vary the input and create the output sequence $o = \{o_1, o_2, ..., o_n\}$:

$$o_j = i_k \; s.t. \; k = argmin_l \{d(v_l, r_j)\} \tag{2}$$

Where $d(x,y)$ is some function that calculates the distance between two points x and y, typically a projected 2-norm (i.e., Euclidean distance). This algorithm is equivalent to the algorithm presented in [1].

In alignment with the literature, we use the Lorenz attractor to generate variations:

$$\begin{aligned} x' &= a(y-x) \\ y' &= x(r-z)-y \\ z' &= xy-bz \end{aligned} \tag{3}$$

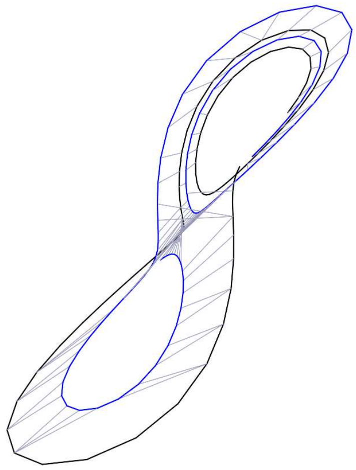


Fig. 1 Reference (black) and Variation (blue) trajectories for $IC_r = (-13, -12, 52)$ (black), $IC_v = (-16, -13.5, 52)$ (light blue) projected on the X-Z plane. The gray lines show the associations between reference and variation points that produce the corresponding variation sequence.

In [3], Dabby investigated other nonlinear systems as well, but found the Lorenz system to be the most desirable. Similarly, we have considered a Rössler attractor, but were unable to convince ourselves that it generated more interesting variations, especially given the short size of our trajectories, which are typically on the order of 30 symbols (moves). After trying several reference ICs and parameters, we settled on the chaotic attractor with $IC_r = (-13, -12, 52)$, $a = 16$, $r = 45$, and $b = 4$. An example trajectory and variation on this system are given in figure 1.

When generating variations, we treat each movement in an input sequence as an individual symbol. To create more diverse and interesting variations we often use multiple climbs as input. This has the effect of both increasing the trajectory length, and incorporating more movement types. Generally, we try to *mix* stylistically similar routes of a compatible difficulty. The result is a variation that takes cues from both routes and is longer than both. In the case that the variation is too long for the application, the setter can simply select a contiguous chunk of the variation of an appropriate length, or eliminate sections that are uninteresting. Explicitly addressing the question of how human setters create interesting short sequences (cruxes), and trying to use this understanding as a basis for a machine learning solution, is left for later work.

A final implementation task is presentation. Clearly, the output from the variation generator needs to be useful not just to a researcher, but to a route setter as well. To this end, we have our variation generator produce a "Chaotic Route Plan" that reproduces the input routes along with the variation and indicates those moves in the variation have been changed and where they have come from (with respect to the input). This route plan can be printed and then used by the route setter as they set a route.

4 Spelunking for Initial Conditions

With variation generation software in hand, our next challenge is choosing an IC_v that results in a variation that is sufficiently different from the input, while preserving the style. To this end, we take a brute-force analysis approach. Given some IC_r, we place points on a NxNxN point grid around it, spaced evenly on intervals of size s. Of the first seven climbs we transcribed, the mean number of moves is 29. Hence, each point on this grid is used as a variation IC to generate a 30 point trajectory. We then study the difference between the reference trajectory and the variation trajectory with respect to two metrics: *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. Generally, $N = 100$ and $s = 0.01$ provides us with a sufficiently complex picture of the IC landscape.

Figure 2 plots these two metrics for a specific instance. We can see that 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—we can see instances where every move is changed, but only by a small amount (purple effect, red change) and vice versa, where a small number of moves are varied by a large amount. In addition to these extremes, there are examples of just about every moderate condition in between.

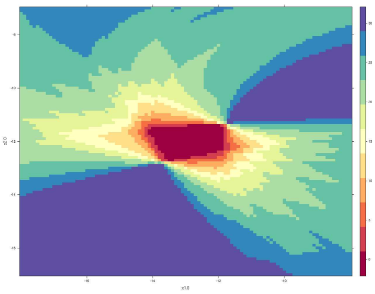
5 Experimental Design and Instrument

To analyze the utility of our proposal, we carried out an experiment in a large commercial climbing gym, the BRC in Boulder, Colorado in collaboration with two expert setters, Tony Yao (T) and Jonathan Siegrist (J), and the editors of *Climbing* magazine.

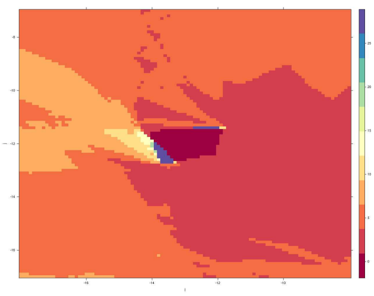
After a small pilot study [7], consultation with the editors of *Climbing*, and the discussion with the setters at the BRC, we decided to set four routes total, two at a grade of 5.10 and two at a grade of 5.11. One of each grade would be set using our chaotic method and the other two would be set traditionally. Using a questionnaire (with incentives for participation provided by *Climbing*), we would measure the attitude of climbers towards the four routes (them not knowing which was which or the nature of the survey). As input to the variation generator, we picked four existing routes in the gym, two of each grade, which were well regarded. All four routes were transcribed by T, and then the two variations were generated by us, using $IC_v = (-16, -13.5, 52)$ and the same IC_r as in the pilot. We also chose to skip the first 100 integrated points of the trajectory to avoid transient behavior.

On September 30, 2009, T and J set the four routes using the plans we generated. Questionnaires were 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.

Over the course of approximately two weeks, 44 presumably unique and blinded climbers completed questionnaires with mean ability (in terms of typical upper-end outdoor climbing grade) of 5.11c[2]. Minimum ability 5.10; maximum 5.12d. On average, a participant has been climbing 12 years with a minimum of 6 months and maximum of 53 years. Additionally, the average participant climbs indoors between 2 and 3 times per week. Although we believe this sample to be fairly 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.



(a) Effect



(b) Change

Fig. 2 Effect and change for $IC_r = (-13, -12, 52)$, $N = 100$, $s = 0.1$ in the x-y plane.

We constructed a questionnaire to interpret climbers' preferences with regard to the routes using standard, well-accepted techniques for construction of attitude surveys [6]. This questionnaire is much more comprehensive than the one used in the pilot study, addressing many of our concerns about scale robustness and consistency, as well as including redundancy to enable external consistency checks. Additional details about this questionnaire are available in [7].

Each climb was analyzed using a 14-item five-point summative Likert scale as well as a single direct ranking question. The five-point response format used the standard response categories (Strongly Agree, Agree, Neither Agree Nor Disagree, Disagree, and Strongly Disagree), which we have assigned ordinal values of (2,1,0,-1,-2) respectively. Four of these questions were negatively keyed so that negative responses indicate positive attitudes. These four questions were inverted in post-processing. Internal consistency analysis found that items 1, 10, 11, and 9 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) indicating a strongly consistent research instrument [12].

[2] This grade is in the Yosemite Decimal System (YDS) notation, which starts rock climbing routes at 5.0 and has no upper bound. The system is subjective and consensus based. The decimal indicates the difficulty. At present, the most difficult route that has been climbed is 5.15b.

6 Discussion of Results

Interpreting the summed Likert scale data as ordinal, we can report the median values for the four climbs, which are given in table 1. Applying a Wilcoxon rank-sum test to the 5.10 scale data we are unable to reject the null hypothesis that the medians are equal (p-value = 0.5448). In the case of the 5.11 climbs, however, we are able to reject this null hypothesis and state that for this sample the difference between medians is significant (p-value $<<$ 0.05). In other words, we 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, which the participants were more indecisive about.

Climb	Setter	Grade	Median Summed Likert Value	Mean Pos. Response Pct.	Median Rank	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	

Table 1 Results of BRC Experiment

Because interpreting summative Likert scale data as ordinal may be contended by some conservative statisticians[3], we also carried out a similar analysis using a convincingly continuous variable: percentage of positive (agree or strongly agree) responses to scale items – an approach common to marketing research. Mean values for this variable are in table 1. Performing a Welch 2-sample t-test on this data produces the congruent conclusions to those above: we are unable to reject the null hypothesis that the 5.10 climbs have equal means but we are 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) of the four climbs are listed in table 1. We computed the inter-grade coefficient of concordance using Kendall's method and found values of W = 0.00937 with p-value = 0.59 for the 5.10 climbs and W = 0.376 with p-value = 0.000644 for the 5.11 climbs. This further serves 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.

It is clear that the participants of the survey preferred climb 3, a climb set with the assistance of our software, over climb 4, a climb set without it. And, 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 input climbs to the variation generator were transcribed by T. This observation leads us to the operating hypothesis that the software performs best when used by the same setter as did the original transcription. Although more work is needed to confirm or deny this, we suspect that a flexible description format like the one we have chosen may allow for 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 that is at least as well regarded as those routes produced without it. And, in some cases, and indeed in this study, it is capable of producing routes that are considered superior by climbers to those set without the software.*

7 Conclusion

In this paper, we have applied chaotic variations to a new domain: indoor climbing route setting. This new domain presents its own unique challenges, which we have discussed. We have proposed new ways of exploring the Initial Condition (IC) space with respect to variation-oriented metrics. We have validated our ideas in a large study at a commercial climbing gym and found that our methods are able to assist expert route setters in producing routes that are at least as well regarded as those set traditionally.

[3] Indeed, the interpretation of Likert-scale data is a contentious issue [5, 2]. Although some researchers claim that a properly composed and applied summative Likert-scale with a sufficient number of questions can produce interval-scale data, we have erred on the side of statistical conservativism. To this end, we use non-parametric tests and treat the summed scale as ordinal, or, use parametric tests that are robust to skew to analyze a continuous variable derived from the ordinal data.

In future work, we are most interested in the prospect of incorporating machine learning into our route generation system, especially as applied to domain specific techniques. Most immediately, we are interested in using natural language processing to parse route descriptions and use this as input to learning systemsthat might be used to identify crux sequences or place transition movements between sequences. Further enhancements and validation will require the support of the climbing community. To this end, we have built a functional prototype of our system that has been released to the public at http://strangebeta.com, and was the focus of an article in the January 2010 issue of *Climbing* magazine.

There are many open questions and much to be done, but the work here serves two important purposes. Firstly, it is a large step forward in terms of creating a functional prototype. And secondly, and perhaps most importantly, it has convinced us and others that chaotic variations are 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.

Overall, we believe that chaotic variations provide great promise in the realm of creative processes. However, in order to understand how these variations can be put to use most successfully, we must approach the problem by adapting existing techniques to new domains, and analyzing their efficacy. Indeed, in this work we found substantial support for the use of chaotic variations in climbing route setting, a result that motivates continued work as well as the investigation of the application of chaotic variations to other creative tasks.

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