Strange Beta: Chaotic Variations for Indoor Rock Climbing Route Setting

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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 which is tuned for our domain and addresses some confounding problems, including a new approach to automatic selection of variation initial conditions. We analyze our system with a pilot study in a small university rock climbing gym as well as 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 which 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 [1, 2, 3, 4]. 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 [5, 6]. In these applications, the sensitive dependency on initial conditions of chaotic systems is exploited to generate a variation which 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 which climbers prefer to those set traditionally.*

The key contributions of this work are as follows:

- A language for the transcription of climbing problems to serve as input to a chaotic variation generator.

- A chaotic variation generator which is tuned for climbing problems and automatically generates easy to use route-plans in an accessible format.
- An exploration of the initial condition (IC) space with respect to sequence variations. And, as a result, an easy to use tool for picking desirable initial conditions given some constraints.
- Development of a robust research instrument for measuring the attitudes of climbers with respect to a route they have climbed.
- Survey-based validation of our system in a commercial climbing gym, in cooperation with expert setters and experienced climbers.
- A publicly available implementation of our software, called *Strange Beta*[1], at `http://strangebeta.com`.

In the next section, we will provide a discussion of the most relevant related work. In section 3, we will give an introduction to the problem domain and define useful climbing related concepts and in section 4 we will give an overview of how *Strange Beta* is used. Section 5 will present our language for describing climbing routes along with its strengths and limitations, and section 6 will review the basic mathematics behind chaotic variations and discuss our implementation. Section 7 will provide our results with respect to exploring the IC space and present our tool for selecting desirable initial conditions. Section 8 will discuss our experimental implementation and analysis of the system in a pilot study in the University of Colorado Outdoor Program's (CUOP) climbing gym. Section 9 provides the experimental design, details, and results of a larger study at the Boulder Rock Club (BRC). Finally, in sections 10 we will discuss future directions and in section 11 we will conclude.

2 Related Work

As mentioned above, using computers in creative tasks, both for independent generation or in assistance roles is not a new idea. Music composition in particular offers a rich history of interaction with computers, both in generative and assistance roles [2]. Comparably, route setting for indoor climbing is a creative task in its own right, requiring substantial expertise in order to produce routes that are of an appropriate difficultly and are interesting to climb. In this work, we are considering a climbing route as a prescribed sequence of dynamic movements – at its core a sequence of symbols from a complex language not dissimilar from a dance choreography or a tonal music composition which can also be thought of as a sequence of symbols.

In particular, we are interested in exploring computer assistance in route setting. Prior work has exploited the sensitivity of chaotic attractors to generate style-preserving variations on sequences. There are two projects, in the realms of music composition and dance choreography, that are especially relevant to our proposal and warrant further discussion.

In [6], Dabby proposed the idea of exploiting the sensitivity of chaotic trajectories to initial conditions to generate chaotic variations on musical pieces. In her work, a musical piece is codified as a sequence of N pitches (symbols). A chaotic reference trajectory on a Lorenz strange attractor

[1]This name stems from the fact that our system makes use of *strange* attractors in order to generate variations on climbing route information, which is colloquially called *beta* by climbers.

is generated at some initial condition (often $(1, 1, 1)$) of length N and each point on the trajectory is assigned to a pitch in the score. Next, a second trajectory is generated, with a different initial condition (say $(0.999, 1, 1)$). For each point in this trajectory, the nearest point in the x-dimension in the reference trajectory is located such that the chosen point is not smaller than the current point. The pitch assigned to this point is used, generating a variation on the original piece that is respectful of the stylistic form of the original. This technique is fairly straight-forward, however, the selection of good initial conditions can be quite a challenge.

In prior work by our colleagues at the University of Colorado in [5], Bradley et al. apply these same ideas to create variations on dance choreographs, but with some necessary domain-specific changes. In this application, a symbol describes the state of 23 joints, which combine to articulate a body position. The nearest neighbor calculation is generalized to two dimensions and without the directional restriction. To smooth dissonant variations, the authors propose a machine learning approach using Bayes networks to find a series of movements that can link two movements in a variation in a way that is "stylistically consonant". They validate their results using a Turing Test and find that the the chaotic variations were only marginally less aesthetic to human judges than those created by human choreographers.

3 About Indoor Climbing

In this section we will give a brief overview of the mechanics of indoor climbing and climbing route setting. Appendix A extends this discussion with a glossary of terms.

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[2], or 8.7 million people, participated in some sort of rock climbing [7].

Indoor climbing walls are installed in configurations and orientations 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 wall at many positions and in any orientation. The arrangement of t-nuts may be on a geometric grid, could be feature-specific, or might be some approximation of uniform-random.

Holds come in all shapes and sizes. Most commonly they are made of polyurethane, but might be made of wood, rock, or other materials. Climbers have a fairly consistent language for describing holds, which while informal involves a relatively small vocabularly 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., side-pulls and Gastons) and an infinite number of possible composite shapes.

Holds are placed on the wall by experienced route setters to form a "problem" with designated start and ending holds. Holds for a given problem are usually differentiated from others on the same wall using colored tape. Some routes are short and some are long. Short routes that do not require a rope for protection are called "bouldering" problems. Longer routes which require mostly side to side movements, are called traverses. The sequence of movements required to climb a given route might not be obvious. Climbers use the word "beta" to refer to information about how to climb a given route (or section of a route).

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

4 Usage Model Overview

Before delving into the details of our system, we wish to describe the prototypical use case that motivates our design. In this scenario, an experienced route-setter uses the *Strange Beta* software to assist in setting a route.

The first step that a route setter must take is to transcribe one or more routes which will be used for input to the variation generator. To this end, she can make use of routes from any domain (i.e., outdoors, indoors, bouldering, etc.) so long as they are transcribed using the computer-readable language we describe in the following section. This can be done offline, and presumably routes transcribed by others can be used as well (although, we will discuss problems with this approach below). These transcribed routes are stored by the software in a sort of route-database so that they can be used as input to the variation generator.

When the day arrives that the setter needs to set a route, she engages the software to pick one or more routes to vary. In the simplest scenario, she will pick a single route, but often we find it is more interesting to pick two or more routes to “mix”. If the 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. With a set of input routes selected, the setter can tweak the controls of the software. In our implementation, these are simplified as a set of presets (“default” and “more variation”). However, the setter can choose to vary the initial conditions or parameters of the algorithm in order to fine tune the output.

The resulting variation is presented as a “route plan”, which is similar in format to the transcribed routes but with several additional annotations that describe how the variation differs from the original(s). If satisfied, the setter can print this plan and use it for direction while setting a route. Variations themselves can be used to generate other variations, or mixed with additional routes to inject other styles. During setting, the setter may choose to make improvisations or corrections to the variation. We imagine that a setter would want such assistance for a host of reasons, foremost among which are creativity block (or simply looking for additional inspiration). We also imagine that such a tool could assist in the training of novice setters.

5 Route Description Language

The first challenge we face is to come up with a descriptive language for climbing problems which 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. An example for a short problem is given in listing 1. In this format, all the text up until the line containing three hyphens is a header which describes the context of the route for posterity, but is ignored (for now) by the variation generator.

In this 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 which 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. As we show in section 9.5, 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. The

```
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.
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
```

Listing 1: Example Route Description File

exception to this rule is for "heel-hook" and "toe-hook" moves where the feet are used to hook larger holds, and in effect are an integral part of the problem they are a part of.

It is worth noting that the way our language is defined, it is more oriented towards a sequence of movements, and less about the specific placements of holds on the wall. The effect of this is that the person who performs the transcription of the route is recording their understanding of how the route should be climbed ("beta") and hence it is a subjective interpretation. It 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 maybe have climbed or set it themselves.

This language certainly succeeds in the goal of being flexible. As compared to the work in [5], 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[3]. 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.

6 Generating Chaotic Variations

To implement our chaotic variation generator, we followed the same basic design used in [6] and [5]. 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 $h = 0.015$:

[3]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.

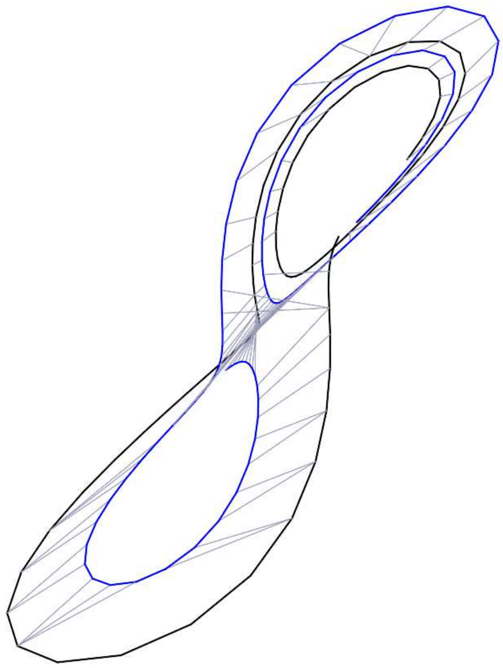


Figure 1: Reference (black) and Variation (blue) trajectories for $IC_r = (-13, -12, 52)$ (black), $IC_v = (-16, -13.5, 52)$ (light blue) projected on the X-Z plane. The gray lines show the associations between reference and variation points that produce the corresponding variation sequence.

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

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 which 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 [5]. However, in [6], the NNA is unidimensional and directional - it will find the nearest neighbor in the x-axis if only and only if the neighbor is greater than or equal to the target. This version has the effect of finding no neighbor for some inputs. In [6], Dabby suggests that in this case the user should fill in the blanks. Our feeling is that this is a needless restriction with uncertain consequences. Although we implement both versions of the algorithm, our preference is for a strict Euclidean NNA of the sort presented in equation 2.

In alignment with the literature, we use the Lorenz attractor (equation 3) to generate variations.

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

In [6], 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. 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 (line) in an input sequence like those in listing 1, as an individual symbol. It is not clear whether it makes more sense to vary the left and right hands separately or together. For this work, we vary them together and save the other approach for future work. Before generating variations there are a few domain-specific limitations that need to be addressed:

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. How should these dependencies be enforced without reducing the chances for interesting variation?

2. What are the implications of short trajectories? How do we generate an interesting variation on a 3 or 5 move problem?

3. In both [5] and [6] the varied trajectory can only contain a re-ordering of the specific set of unique symbols in the reference trajectory. In a potentially large language of possible movements, how can we bring "new" or "unique" movements into a variation trajectory?

To approach the issue of matches, we simply replace "match" moves with the previous movement with the other hand and add a note to the move "(match?)" which lets the setter know that this move was used as a match move in the input problem. We address the second two issues by using 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 which 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" which reproduces the input routes along with the variation and indicates which moves in the variation have been changed and where they have come from (with respect to the input). Figure 2 shows a screenshot of the (web based) software in the process of generating a variation on two input routes. In this figure, the chaotic route plan is shown, which gives a picture of the corresponding trajectories, some details about how it was generated, and the varied movements along with their deltas (the distance they have moved as a result of variation). This route plan can be printed and then used by the route setter as they set a route as we have described in section 4.

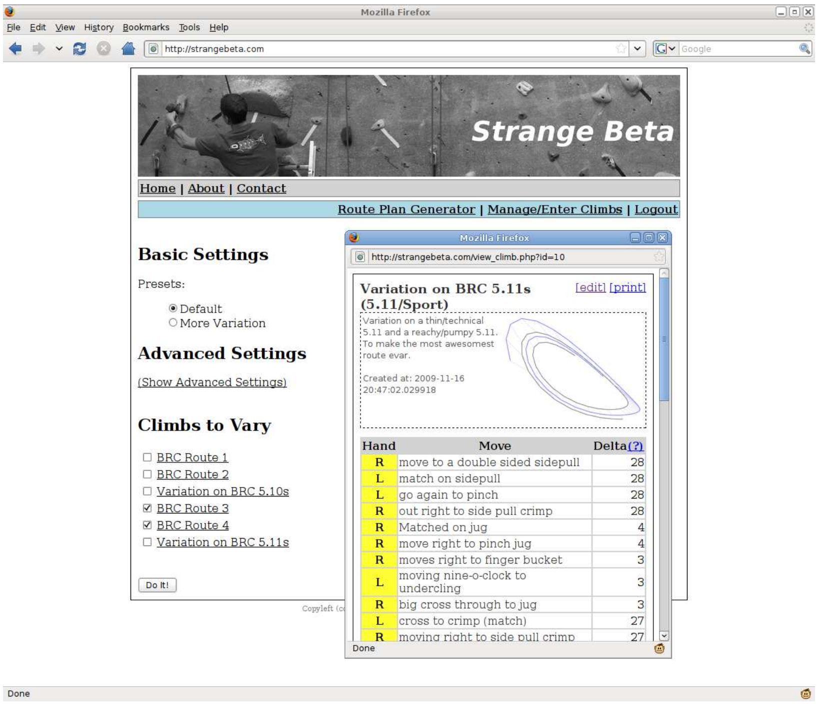


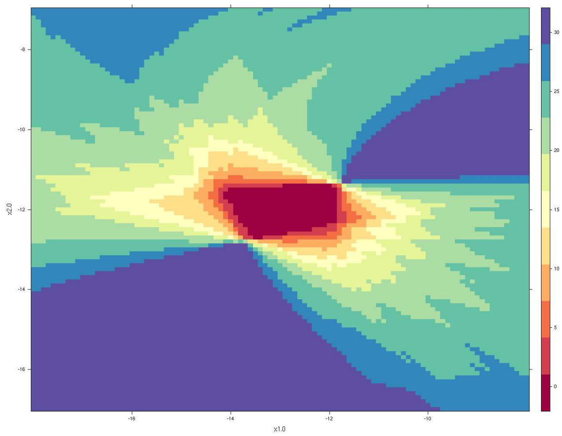
Figure 2: Screenshot of *Strange Beta* software being used to generate a variation on two input routes.

7 Spelunking for Initial Conditions

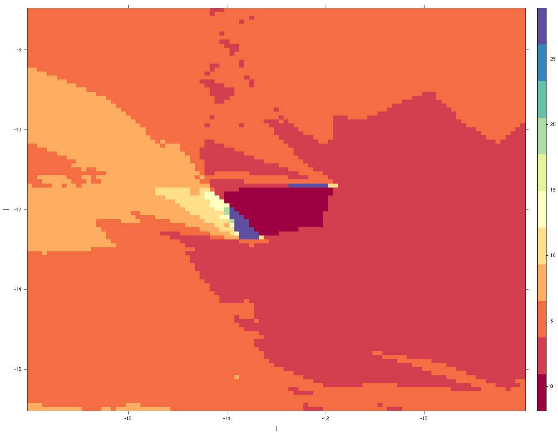
With variation generation software in hand, our next challenge is choosing an IC_v which results in a variation which is sufficiently different from the input, while preserving the style. To this end, we take a brute-force analysis approach. Given some IC_r, we place points on a NxNxN point grid around 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 which 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.

This task, however, requires a great deal of computation and produces a substantial amount of data – $N = 100$ results in 1,000,000 unique ICs and therefore 1,000,0001 runs of an ordinary differential equation (ODE) solver on equation 3. Thankfully, this problem is easily parallelizable. To compute the results in a tractable amount of time (30 minutes versus 2 days), we made use of a 16 node, 128 CPU compute cluster, with each of 100 nodes computing 10,000 trajectories.

Figure 3 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) Effect



(b) Change

Figure 3: 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 a 2-space version of Euclidean distance for nearest neighbor calculation.

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.

It is worth noting that the plots in figure 3 are by no means typical. We generated similar plots for different s values, different NNAs, and in different projections (clearly we must project because these metrics are 4-dimensional). Each combination generates a holistically different picture. However, the combination in figure 3 provided a representatively complex change and effect space, which is why we limit our later analysis to this IC_r, the 2-dimensional Euclidean NNA, and generally the $IC_v = (-16, -12, 52)$ (which is drawn left of center in figure 3.

For general purpose (or automated) picking of an appropriate IC_v, we also implemented an "IC picker" tool which sifts through the large amount of data (after some preprocessing has been done to speed this process up) and finds candidate ICs for a desired amount of change or effect. This automates the otherwise grueling process of sifting through dozens of plots, or randomly trying points, in order to find a point which is appropriate for your needs. It also makes it easy to find multiple, possibly disparate, points with similar change and effect characteristics. Explaining the qualitative differences in cases like these, in terms of their effect on the generated variation, is a problem for future work.

8 Pilot Study

With route plans in hand, we want to analyze the effectiveness of the system. After negotiations with the route-setting staff at the CUOP climbing gym, we were invited to come set routes with them. On April 24th, 2009 we set a 29-move traverse called "Green-13", which is based on a variation of the route in listing 1 and a long roped route (a green-taped 5.12-[4] at the Rock'n and Jam'n gym in Thornton, Colorado). The routes are of a similar style, both making use of many

[4] "5.12-" indicates the difficulty of the problem in the widely used Yosemite Decimal System (YDS) subjective scale, where the easiest problems requiring a rope are given 5.0 and there is no upper bound, with the currently "most difficult" climb rated 5.15. The postfixed minus, in this case, indicates that the route is on the "easier end"

crimpers, and having a fairly sustained intermediate difficultly. We used $IC_v = (-16, -12, 52)$ and $IC_r = (-13, -12, 52)$. During route setting, we attempted to stay as true to the variation as possible, but made adjustments where appropriate. For instance, if a move could be modified slightly[5] to make use of a hold already present on the wall, we were willing to make that modification. The beginning few moves had to be changed slightly, because the variation had placed the crux of the green-taped 5.12- at the beginning of the variation, and having the crux at the very beginning is not much fun for climbers. The order of R and L had to be changed several times to make movements more interesting or avoid awkwardness.

The result is a climb which still required a fair amount of human thinking by the setter, but with a different focus than is typical for climbing route setting. The staff setters who were also in the gym were clearly envious. Typically, they try to think up a particularly interesting move or two and then build a problem around it. By using the route plan, we did not have to be creative on a spontaneous basis, which we argue makes it easier to set problems. In [6], Dabby describes her system as an "idea generator"; based on our experience here, *Strange Beta* succeeds on that basis.

To determine the quality of the route we set using the chaotic variation, we placed a questionnaire in the climbing gym which asked climbers to compare three routes on each of five metrics, using a scale from one to five (i.e., a weak Likert scale with a Likert-type response format). All three routes are of comparable length and difficulty, but one is our Green-13 and the other two were set by expert human setters. The participants were not informed the purpose of the survey, or the difference between the routes.

Six climbers chose to complete the voluntary questionnaire, one of which was not blind (one of the staff setters). Appendix B provides details about this questionnaire. Although the sample size is small, it is sufficient for our needs in terms of a pilot study. To analyze the consistency of the instrument, we computed Cronbach's $\alpha = 0.817$. Doing a per-item consistency analysis, we determined that question 5 was the least consistent, so we discarded it from analysis, producing a new overall $\alpha = 0.866$. Although this is a respectable α value, we will not claim great confidence in this instrument because it is only a five item scale, which is smaller than is recommended in the literature. Treating the summed scale data as ordinal, we can report median attitude values, which are summarized for the three routes in table 1. Climb 3, a traditionally-set route, appears to be the winner. To determine if the difference in these medians is significant, we used a Wilcoxon rank sum test. The results show that the difference in medians between our climb and the other two climbs is marginally significant (p-values of 0.061 and 0.0242 for climbs 2 and 3 respectively), but the difference between the two non-chaotic climbs is not significant (p-value = 0.371). Hence, we can conclude that at least for this (small) sample, the non-chaotic routes were preferred, but not by a substantial margin.

As is usually the case with pilot studies, our conclusions only serve to nominate new questions:

- Green-13 was set by an inexperienced route setter (your author), what would experienced route setters think of using the chaotic variations to set routes?
- What about setting routes at varying levels of difficulty, different styles, or different lengths?

of the 5.12 grade. Although the 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.

[5] In this case, by a "slight" modification, we mean without substantial change to the periceived "intent" of the variation.

Climb	Median Summed Scale Value	Chaotic
1	14	X
2	15	
3	16.5	

Table 1: Results of Pilot Survey

- Is there a qualitative relationship between the choice of IC and the resulting variation? Can this be controlled or quantified?
- Are there other, more prescriptive, description languages which result in more interesting variations?
- Can we use machine-learning to replace some or all of the subjective human elements in setting from a variation?

To attend to some of the questions and to address limitations in survey apparatus, we performed a much larger study at the BRC, which is described in the next section.

9 Experiment and Analysis

Following is a description and results of a more substantial experiment we carried out at a large commercial climbing gym, the Boulder Rock Club (BRC) in Boulder, Colorado in collaboration with two expert setters, Tony Yao (T) and Jonathan Siegrist (J), and the editors of *Climbing* magazine.

9.1 Experimental Design and Instrument

After some consideration, and consultation with the editors of *Climbing* and 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[6].

On September 30, 2009, T and J set the four routes using the plans we generated, and afterward we interviewed them to record their thoughts on the experience, which we have summarized below. 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)

[6] These two changes from the pilot study were intended to produce routes with more variation.

Climb	Setter	Grade	Med. Summed Value	Avg. Pos. Response %	Med. 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 2: Results of BRC Experiment

of 5.11c. 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.

We constructed a questionnaire to interpret climbers' preferences with regard to the routes using standard, well-accepted techniques for construction of attitude surveys [8, 9, 10]. 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. Appendix B provides additional details about this questionnaire. 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 [11, 12].

9.2 Climb Preference

Interpreting the summed Likert scale data as ordinal, we can report the median values for the four climbs, which are given in table 2. 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[7].

[7] It is work nothing that the setter of the 5.10 climbs, J, was very displeased with his "chaotic" route. It is interesting to note that while individual climbers may have preferred one route or another, on the whole, they were ambivalent about the two 5.10 routes. One possible hypothesis, proposed by the climbers we worked with, is that climbers are less decisive about the quality of less difficult routes.

Because interpreting summative Likert scale data as ordinal may be contended by some conservative statisticians[8], 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 2. 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 2. 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 which 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.

9.3 Possible Correlating Factors

In addition to determining climb preference, we also made use of correlation tests to answer a pair of lesser research questions:

- Is preference effected by climb order (i.e., do participants rate climbs more or less well when they are tired)?
- Is preference effected by climber ability (i.e., do better or worse climbers rate climbs more or less well)?

To address the first question, we use Kendall's tau on the ordinal variable and Pearson's r on the continuous variable. The result is a correlation very near zero and with high p-values. From this we conclude that there is no obvious correlation between climb order and climb preference (or more precisely, we cannot reject the null hypothesis that they are uncorrelated). We also confirmed this conclusion using the pure ranking data, which produces a Kendall coefficient near zero and a large p-value (near 0.95).

For the second question, we used the same tests as above. We see small 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. However, the results above seem to indicate that these concerns are unfounded.

9.4 Results Summary

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

[8]Indeed, the interpretation of Likert-scale data is a contentious issue [13, 14]. 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 which are robust to skew to analyze a continuous variable derived from the ordinal data.

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 which 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.*

9.5 The Setters' Experience

In addition to the preferences of climbers, the opinions of the route-setters about the process of setting routes from chaotic variations are crucial to understanding effectiveness of the system as a whole. To this end, we interviewed the setters after they had finished setting the four routes. One setter, J, found using the generated route plan to be unwieldy and time-consuming, perhaps a result of having the other setter, T, transcribe all four input routes. 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 the composers in [6], but at odds with the more supportive response dancers had to a similar experiment in [5].

During the course of the experiment, we have identified several ways to improve the route plan format and route transcription to attend to problems the setters encountered using the system. Principally, we feel that a setter will have the greatest success using variations generated from routes she transcribed herself. Also, the setters found some aspects of the output format to be confusing (principally the inclusion of the input data), which we have since removed.

To address to our initial assumptions about the sparsity 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 feet 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.

10 Future Work

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 systems which might be used to identify crux sequences or place transition movements between sequences.

There has been some academic research on rock climbing in other fields which 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 which might be used to generate route variations aimed at specific training goals [15]. Although largely preliminary, there has been some effort to build biomechanical models for equilibrium acquisition while climbing [16]. 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 [17].

Further enhancements and validation will require the support of the climbing community. To this end, we have built a functional prototype of our system which is being released to the public at `http://strangebeta.com`, and will be the focus of an article in the January 2010 issue of *Climbing* magazine.

11 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 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.

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 of such a system. 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 which motivates continued work as well as the investigation of the application of chaotic variations to other creative tasks.

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A Glossary of Climbing Terms

- **Jug** - A fairly deep hold whose topology is similar to that of a steep-walled pot or jug.
- **Crimper** - A shallow hold which may only support the tips of the fingers and might need to be locked-off (where the thumb reinforces the position, by pressing down on the forefingers)
- **Sloper** - A more rounded hold which is gripped with the palm of the hand or pads of the fingers, to create friction.
- **Jib** - A very small knob-like hold, usually used as a foot piece.
- **Sidepull** - When a hold is positioned so that its main gripping surface is away from the climbers body. Similar to the grip one would use to close a sliding glass door.
- **Gaston** - The opposite of a sidepull, with the gripping surface facing inward. Best explained as the grip used to pry open an elevator door.
- **Redpoint** - To climb from start to finish without falling, and typically placing protection on the way.
- **Problem** - Another term for a climbing route which more directly captures the often puzzling nature of climbing routes.
- **Match** - A hold which is held with both hands simultaneously.
- **Beta** - Information about how a route/problem must (or can) be climbed.

B Questionnaire Design and Consistency

The questionnaire used the pilot study makes use of a five-question Likert scale with a five-item Likert-type response format to determine the attitude of climbers. The questions used in this scale are listed in table 3 along with Cronbach's α, a measure of internal consistency. The α reported in this table is the overall Cronbach's α, with the given question removed, hence a number larger than the overall $\alpha = 0.817$ indicates that censoring this question would improve the scale's consistency [11, 12]. We also asked participants to state whether they were a Beginning, Intermediate, or Advanced climber, but did not use this information in our analysis.

The BRC questionnaire makes use of a 14-question Likert scale with a five-item Likert response format to determine the attitude of a participant towards a particular route. The 14 questions, which are grouped into four categories, all are aimed at determining whether a participant enjoyed a particular route and to what degree. Table 4 lists the questions along with their internal consistency metrics. In addition to the α value, which is relative to the overall $\alpha = 0.708$, τ is the Kendall's τ correlation coefficient for this question's rating as correlated with the overall rating – a larger correlation coefficient indicates that the question is more consistent [8].

In addition to the Likert scale, the questionnaire collects some domain-specific demographics, and asks participants to rank-order the climbs (which serves as an external consistency check) and list the order in which they climbed them (which serves to document any ordering bias). These questions are listed in table 5.

No.	Question	α
1	Appropriate Difficulty	0.725
2	Sustained Difficulty	0.727
3	Has Good Flow/Seems Consonant	0.810
4	Is Creative/Has Interesting Moves	0.755
5	Requires thought/Non-obvious Beta	0.866

Table 3: 5-item Likert scale used in pilot and internal consistency information

No.	Question	Category	τ	α	Neg.
1	Too easy for the grade	Difficulty and Rating	-0.108	0.750	X
2	Too difficult for the grade	Difficulty and Rating	0.184	0.703	X
3	Difficulty is consistent throughout the climb	Difficulty and Rating	0.220	0.696	
4	Requires thoughtful/nontrivial beta	Difficulty and Rating	0.117	0.707	
5	Has good flow throughout	Flow and Variety	0.536	0.661	
6	Appears to be well thought out	Flow and Variety	0.556	0.650	
7	Is creative/has interesting moves	Flow and Variety	0.480	0.657	
8	Climbs awkwardly	Flow and Variety	0.413	0.668	X
9	Good variety of handholds/types of grips	Flow and Variety	0.161	0.705	
10	Has a definite crux	The Crux of It	-0.121	0.753	
11	Crux is technically engaging	The Crux of It	0.043	0.719	
12	Has an unpleasant/stopper crux	The Crux of It	0.173	0.701	X
13	Is a route I would climb again	Summing It Up	0.560	0.645	
14	Is a route I would recommend to others	Summing It Up	0.633	0.638	

Table 4: 14-item Likert scale and internal consistency information

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Question
Years climbing?
Years climbing in a gym?
Hardest indoor redpoint?
Hardest outdoor redpoint?
Days/week climbing outside?
Days/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 5: Demographics and other questions

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