Modelling Affordance based on Physical Characteristics

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Abstract

As climbing continues to grow rapidly in popularity, climbers must develop a heightened awareness of their own physical capabilities and limitations. Unlike disciplines that rely on standardized motion patterns, climbing demands that climbers dynamically and quickly adjust their movement strategies to reach the goal as quickly as possible based on their individual physical characteristics such as height, arm span, and leg span, and requires continuous decisions about which holds are reachable by the hands or feet and how to progress towards a target while remaining balanced. We study this problem on multiple fixed walls whose annotations consist only of hold shapes. We estimate the center coordinates of the grab point by using the coordinates provided for each vertex, and we synthesize a start configuration by randomly selecting holds because no start holds are provided. A Graph Neural Network (GNN) is utilized to label every hold as unreachable (0), only hands reachable (1), only feet reachable (2), and both hands and feet reachable (3) by using geometric features derived from the current limb positions and normalized by the climber’s anthropometrics, such as height, ape index, arm span, and flexibility. On top of these predictions we compare two planners, the first one is a greedy baseline that moves hands and feet simultaneously toward the goal while keeping feet below hands and always select the furthest holds, and the other one is a posture-aware planner that moves one limb type at a time, prefers hands above feet, and encourages vertical alignment between hands and feet centers via an angle threshold and alignment cost.

We evaluate three different cohorts, which are casual, skilled, and elite, and each cohort is with 100 simulated climbers on the same wall, start, and goal. Using bar charts, we summarize completion rate, and average steps to goal for successful trials, including stratifications by key anthropometric factors. The results show that performance differences are driven primarily by individual body attributes, such as arm span, leg span, height, and ape index, rather than the cohort label alone. Climbers with larger effective reach complete more frequently and in fewer steps. The greedy planner achieves higher completion rates, whereas the posture-aware planner yields more vertically balanced sequences at the cost of success on some instances, which reveals a practical trade-off between progress and stability. We provide an evaluation protocol and analysis that can inform route setting and training feedback for different ability levels.

Ethics Statement

After discussing with my supervisor, we plan to use the dataset that contains the climbing route with hold points from [Kaggle](https://www.kaggle.com/datasets/tomasslama/indoor-climbing-gym-hold-segmentation/data) and simulate the climbers with different attributes in our research. Therefore, this project that do not require ethical approval at all, because it does not collect or process any relevant data.

Supporting Technologies

* Programming Environment: Code was developed using a recent version of Python 3 with Jupyter notebooks and plain scripts, utilizing data science libraries such as NumPy and Pandas.
* Deep Leaning Framework: PyTorch for model definition, training, and inference, tensors for moving CPU/GPU, and PyTorch Geometric for graph ops and batching.
* Version Control: Git with a GitHub repository was used to ensure that the project is securely stored and documented in the cloud.
* I used LaTeX through the online service Overleaf for the formatting of the thesis.

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Chapter 1

Introduction

This chapter opens with background on indoor climbing and motivates climber-conditional reachability analysis as a tool for route setting and training. We then discuss the limitations of evaluations based on hierarchical or single-strategy assessments and introduce our approach. A graph neural network based on anthropometric data is combined with two planners, which are a greedy baseline planner and a pose-aware strategy planner. Finally, we highlight development challenges (centroid approximation, synthetic starts, and planner hyperparameters) and outline the research aims on ability-group differences, policy trade-offs, and sensitivity.

* 1. Project context and problem

Indoor climbing success depends jointly on wall geometry, holds affordances, and a climber’s body[1]. Route levels summarize difficulty for an average person, but for setters and coaches, they often need a more precise answer to who can do what, how can do it, and in how many steps[2]. A computational pipeline is built for a fixed wall with annotated holds, a start and goal, and simulated climbers described by anthropometrics, which is to predict whether the goal is reachable, and how many steps it will take under a chosen movement strategy.

We represent the wall as hold graph whose nodes hold centroids that are derived from the provided shapes and whose edges connect spatial neighbors. A reachability model is built by graph neural network, labels each hold as unreachable, hand-reachable, foot-reachable, or reachable by both, which is inspired by Nishad[3]. On top of these predictions, we generate motion sequences using two planners. One is a greedy baseline that moves hands and feet simultaneously toward the goal and keeps feet below hands. The other one is a posture-aware planner that moves hands or feet at a time, and encourages vertical alignment between hand and foot centers through an angle threshold and alignment cost. For evaluation, we simulate three cohorts (casual, skilled, elite) of 100 climbers each, sampled over realistic anthropometric ranges[5][6][7], such as height, ape index, weight, and strength.

* 1. Practical and Methodological Implications

Simulating reachability rather than relying on rough grades brings two immediate benefits, which are route setting and training feedback. For route setting, setters can test whether a proposed route is unfairly biased towards a specific body type, especially the climbers who are taller and have longer arm spans[2][8], and identify where to add intermediate footholds or handholds to reduce the impact of physical differences[4]. For training feedback, coaches and climbers receive targeted guidance. For instance, when performance is limited by poor foot follow-through rather than hand reach[1], or when movement patterns consistently violate upright posture and cause instability[9]. Coaches and climbers can use this feedback to tailor training, such as building strength or improving hold point selection.

The broader significance of this work lies in its methodological contribution. We present a lightweight and transparent tool that integrates two complementary components: a learned model of local hold affordances, which is implemented as a graph neural network, and a set of explicit motion rules encoded in path planning algorithms. This design allows performance results to be clearly traced back to the decision logic of the GNN’s predictions or planner, e.g. whether the goal can be reached by climber or the number of moves required. This traceability not only facilitates targeted optimization of models or rules, but also enhances the system's interpretability and reliability for setters, coaches, and researchers.

* 1. Prior work and selected approach

The classic difficulty assessment method is a combination of expert judgement and coarse statistical data, such as height and grade[8]. Recent research on accessibility and posture planning has prompted us to learn about the reachability of each grip point based on the climber’s condition, and then plan based on these predictions[1][12]. Our approach follows the two-stage design for transparency and speed: Climber-conditioned reachability and Policy-level simulation.

For Climber-conditioned reachability, the GNN predicts unreachable, hand reachable, foot reachable, and both reachable labels for each hold by mixing features of the distance between the current position and the current hands/feet position, and normalizes them based on the range of arm and leg reach. Anthropometric vectors, such as height, ape index, spans, flexibility, and leg-length factor, modulate the node embeddings. Thus, the same wall will produce different reach maps for different climbers[3][11].

For Policy-level simulation, we apply two simple and interpretable planners, rather than solving full-body dynamics. The first planner is greedy progress, which can achieve the fast expansion of the reachable frontier[4]. The second planner is posture-aware, which achieves softer progress but higher likelihood of hands-over-feet and near-vertical alignment[12].

This kind of separated design allows us to study trade-off between progress and stability and attribute failure to limitations in model coverage or conservative movement choices by planners.

* 1. Central Challenges
* Sparse supervision and geometry: The dataset from Kaggle contains hold shapes (the coordinates of each vertex) but no official start configuration. We approximate each hold by its centroid and generate a synthetic start, which may miss directionality/friction effects of real holds.
* Coupling perception and policy: A model will mark many holds reachable based on provided position, but a conservative strategy may result in a deadlock. Conversely, an aggressive strategy may succeed without strict posture control. It is hard to clarify these relationships.
* Fair comparisons across abilities: To ensure differences reflect body attributes and policy rather than random initialization, we fix the walls and goals and evaluate all cohorts on the same set of initial states. In contrast, randomized positions of climbers were employed in training to produce labels and broaden coverage.
* Hyperparameter sensitivity: New knobs are introduced in posture-aware planning, such as angle threshold, and alignment weights, which can shift the balance between success and stability.
  1. Research Aims
* Learn hold affordances conditioned on the climber: Train a GNN that tags each hold as unreachable, hand reachable, foot reachable, or both reachable by using current position and climber’s attributes.
* Compare two movement strategies on the same predictions: Implement a greedy policy, which moves both hands and feet simultaneously and always selects the closest reachable hold to the goal. In addition, a posture-aware policy also needs to be implemented, which moves only one limb type at a time, considers the body’s balance when attempting to move to the closest reachable hold to the goal, such as keeping the body as vertical as possible, and also considers whether the four hold points are reasonable.
* Establish a reproducible evaluation protocol across abilities: Simulate casual, skilled, and elite cohorts (100 each) on a single wall with same start and goal to record the completion rate and the number of steps to goal (success: number of steps, failure: -1).

Chapter 2

Background

This chapter establishes the technical background for our study and positions it within prior work. We first review core climbing biomechanics, such as height, ape index, and flexibility, and how to set hand/foot reach and stable posture, also including a standing-reach that we later use for over-stretch guarding. We then model a wall as a graph of holds, explain our state-dependent node features that are recomputed after each move, and motivate casting per-hold affordances as a four-class node classification problem with a GNN. Building on these predictions, we contrast two lightweight planners: greedy and posture-aware. We then discuss assumptions about static and dynamic reach, and describe our synthetic supervision pipeline. The chapter closes by identifying research gaps and explains the basis for our evaluation protocol and design choices.

2.1 Climbing Biomechanics

Climbing movement is fundamentally geometric. Thus, feasible actions depend on where the wall’s holds lie relative to the climber’s body[16]. In our experiments, we assigned six anthropometric factors to all climbers, which are height, weight, ape index, strength, flexibility, and leg length factor. In practice, we only used height, ape index, flexibility, and leg length factor. Height and arm span (height × ape index) set the range for hand reach[11], flexibility and leg span (height × leg length factor) expand foot reach and high-step range[14], and ape index summarizes upper-limb advantage.

We use an analytic reach oracle to test whether a hold is reachable by hands or feet given the current contacts[11]. On top of these predictions, we evaluate two planners – greedy baseline and posture-aware planner. For the greedy planner, it moves hands and feet simultaneously to reachable holds closest to the goal in a step, enforce feet below hands, and there are no posture cues, which accelerates progress but can produce stretched poses[4]. For the posture-aware planner, it will consider the positions of hands and feet, which will keep feet below hands as much as possible[9]. In addition, it can monitor the angle to vertical between hand and foot centers[14], and it can guard against over-stretch by checking whether vertical hand-foot separation exceeds a given threshold of standing reach. When this “reach guard” triggers, we move whichever limb center is farther from the goal to bring the body back to a reasonable range[13]. These heuristics are simple, interpretable surrogates for fuller balance models and match common coaching cues[13][15].

2.2 Modeling a wall as a graph of holds

Each wall is represented as a graph, whose nodes are holds (we use hold centroids parsed from region shape attribute) and whose edges connect spatial neighbors, e.g. KNN. This supports local message passing and keeps the model invariant to permutations of holds[17].

Node features in our implementation are state dependent and get recomputed after every simulated move:

* Centroids of hold: (x, y)
* Distances from the node to the current hands and feet: both the mean and minimum, each normalized by the climber’s arm reach or leg reach.
* Binary flags: marking whether the node is currently used by a hand or a foot.

This encoding exposes the GNN to the instantaneous affordances of the state by indicating the position of new support points relative to the currently established support base without explicit dynamic information[3].

2.3 Per-hold affordances with GNN

We cast reachability as node-wise affordance classification with four classes, which are unreachable, hand, foot, and both (0, 1, 2, 3 in the logits’ argmax). The model performs message passing over the hold graph and outputs a logit vector per node[19].

Supervision via synthetic starts. Rather than relying on a single official start, we generate (K=20) randomized initial limb configurations per climber-wall pair under simple constraints[14]. For each sampled start and each set of anthropometrics, we label every hold with the reach function. This random augmentation method generates a large and diverse training set, which enables GNN to encounter a wide range of relationships between bodies and walls[20]. In our typical scale before filters: 100 climbers × 15 walls × 20 starts = 30000 graphs per cohorts.

2.4 Lightweight planners on top of the GNN

We evaluate two simple planners that generate a series of interaction sequences based on the classes predicted by GNN. These two planners reevaluate the graph features and rerun GNN after each move[19][21].

2.4.1 Greedy planner (progress-oriented)

* In each step, this planner will pick two hands and two feet among nodes predicted reachable, prioritizing closest-to-goal choices while keeping feet below hands[4].
* Hands and feet move simultaneously in a step.
* Tends to maximize upward progress, often high completion, but can be stretched, and less stable postures[14].

2.4.2 Posture-aware planner (stability-oriented)

* Move one limb type at a time: if the hand-foot center line deviates from vertical beyond a threshold, move feet to realign under the hands, otherwise move hands[12].
* When moving hands: prefer candidates above the feet (with a small vertical margin) and choose a pair that is close to the goal.
* When moving feet: prefer candidates below the hands, exclude occupied hand holds, and choose the pair that can minimize a center alignment cost plus a goal proximity term[22].
* Standing-reach guard: if vertical hand-foot separation is too large, override the choice and move the limb type which is farther from the goal first.
* This policy explicitly encodes uprightness and “hands-above-feet” structure, typically yielding more balanced sequences at a potential cost in success[13].

Based on these two planners, we also provide the non-visual calculation to return the number of steps to success or -1 on failure, which enables large batch evaluation.

2.5 Affordances in climbing

Affordance theory understands perception from the perspective of the opportunities for action provided by actors and their environment. In climbing, a hold affordance refers to a point that climbers can grip or step on relative to their own bodies and the current contact point. This frame justifies predicting per hold affordances (unreachable, hand, foot, and both), the affordances of all other holds will change by using state-dependent node features when the base of support changes. It also explains why simple geometric cues, such as feet-below-hands, and vertical alignment, can approximate more complex balance models[23].

2.6 Static and dynamic reach

Sport science distinguishes static reach (static posture, no swing) from dynamic reach (momentum). Our oracle and planners target the static and semi-static regime typical of controlled modern moves. This choice can produce consistent labels and aligns with graph-based reasoning. However, it could underestimate explosive jumps and sequences that require high coordination, so that this is a known limitation and a direction for future research[16].

2.7 Anthropometry and standing-reach normalization

Height and arm span set first-order upper-limb reach, ape index summarizes their ratio, flexibility (hip and ankle flexibility) and leg span govern high-steps and body elevation. A simple standing-reach approximation from dataset on anthropometric measurements[26]:

Supports body-scaled normalization and our 75% guard against over-stretch. Normalizing distances by arm and leg reach makes features more comparable across climbers and reduces fake correlations related to absolute pixel scales[26].

2.8 Label generation with synthetic starts

In the absence of official starts and measured athletes, we adopt a fully synthetic supervision strategy: walls are abstracted by hold centroids, climber anthropometrics are sampled from plausible ranges, and an analytic reach oracle provides per-hold affordance labels under randomized initial states. This yields broad coverage of body–wall–state combinations and motivates our per-node, state-dependent formulation[25].

2.9 Research Gap

Although the popularity of rock climbing has attracted a large number of researchers to conduct calculations and analyses, several gaps remain:

* Lack of per-hold, state-dependent, individualized affordances: Prior work typically predicts route difficulty or aggregate success for an average climber, or studies generic affordances, but does not model reachability at the hold level as a function of the current positions and explicit anthropometrics. To our knowledge, there are currently no studies using GNN to output node-level labels that simultaneously satisfy state conditions and climber conditions.
* Limited, interpretable posture modeling in planners: Most planning baselines are greedy toward the goal or rely on untransparent policies with little explicit treatment of posture and stability. We did not find a systematic evaluation of simple, interpretable geometric cues as planning constraints layers over learned affordances.
* Spare supervision strategies for state space: Existing datasets barely provide dense state labels across many starts. There is a gap in scalable supervision, which utilizes an analytical reachability oracle to label each hold state for each climber-wall pair across multiple random initial states, so that the model can learn how reachability changes as the support set changes.
* Cohort-level evaluation that cleanly separates ability from initialization: Comparative studies across ability levels are rare and often confounded by different starts. It is imperative to establish a protocol for fixed walls and goals, apply multiple initial conditions to each climber-wall pair, and summarize the results to ensure that the observed differences reflect physical characteristics and policy influences rather than just initial condition specificity.
* Outcome metrics beyond completion only: Many works report success/failures but omit the distribution of the number of steps to goal, which is crucial for training feedback and route setting.
* Reproducible, lightweight pipelines: Prior studies often lack open, modular setups where one can adjust angle thresholds, vertical margins, and alignment weights. A simple, reproducible pipeline is missing for broad cohort and hyperparameter-level analysis.

Chapter 3

Methods

3.1 Data & Preprocessing

In our project, the data we used contains climbing walls, climbers with anthropometrics, and initial states. The climbing walls are sourced from Kaggle, while the climbers with anthropometrics and initial states are simulated by us.

3.1.1 Climbing Walls

The initial data for the climbing wall consists of multiple hold points, with each row representing a hold point. A hold point is a polygon composed of multiple vertices, which are represented by x and y coordinates. We first remove empty walls (walls with zero valid holds) to avoid noisy, degenerate examples and reduce dataset size. Then, we consolidate the holds belonging to the same wall into a single record (one row per wall), which shortens the dataset while increasing unit depth (all holds of a wall are stored together). This structure simplifies downstream batching and makes us compute wall-level diagnostics once. In addition, we build a shapely.geometry.Polygon and extract interpretable 2D descriptors for each hold polygon, which are area, perimeter, aspect ratio, and circularity. These features further enhance node attributes by adding simple, easy-to-understand geometric shapes that are associated with holding. What’s more, we compute the centroid (x, y) for each hold, yielding the wall’s set of hold centers:

3.1.2 Climbers

At the beginning of the project, I reviewed a lot of literature and browsed through many climber data from rock climbing projects, but I could not find any suitable climber data with anthropometrics. So, for the climbers’ data, we used simulated data, which was generated by Python simulations. We divide climbers into three different skill levels: casual, skilled, and elite. For each climber in each level, we sample several attributes based on different ranges to each climber.

Table 1: Simulated climber attributes by skill level

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Climbers | Height | Ape Index | Weight | Strength | Flexibility | Leg Length Factor |
| Casual | 165±5 | 1.00±0.03 | 70.5±14.78 | 70±10 | 4-6 | 0.5±0.05 |
| Skilled | 170±5 | 1.02±0.02 | 69.9±10.24 | 85±10 | 6-8 | 0.51±0.06 |
| Elite | 177±8 | 1.05±0.03 | 67.2±13.6 | 105±10 | 8-10 | 0.53±0.05 |

From the character attributes in Table 1, we also extend the arm span (Height \* Ape Index) and leg span (Height \* leg length factor). Arm span determines the effective reach envelope of the upper limbs, directly constraining the set of holds that can be contacted with the hands[11]. In theory, climbers with a longer arm span relative to their height (higher ape index) are usually able to bypass the middle foothold and utilize a wider grip position. In contrast, leg span governs the maximum high-step and the ability to reposition the lower body upward. A greater leg span and leg length factor allow climbers to stabilize postures by maintaining feet below hands and to reduce over-stretch during upward progression[27]. These factors collectively constitute the core anthropometric determinants of individual reachability, which are the essential predictive indicators in our modelling framework.

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