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 & Related Work

This chapter provides the foundations for our study. We outline key climbing biomechanics (height, arm span, ape index, flexibility, etc.) and how they shape reach and stable posture, model routes as hold graphs with state-dependent features, and review GNNs for per-hold affordance prediction. We then contrast two different planning styles – greedy progress and posture-aware stability. Finally, we describe our evaluation on fixed walls and goals using multiple randomized initial states per climber-wall and large cohorts, aggregating outcomes across starts. And reproducibility is supported by published code and configuration details.

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,

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