

Identification and Classification of Holds for a Rock Climbing Wall

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Abstract

This project was created to analyze rock climbing walls in the real world and recreate, modify, and traverse them in the digital world. This is done through a series of steps from image collection, hold detection and classification, route planning, and AI traversal.

1 Introduction

The project is currently a work in progress as of the date of this paper. Current progress includes hold detection and classification by color with few errors on 2D images of rock climbing walls. The project is now testing the use of the detection and classification algorithm on live video streams. Preliminary work has begun to classify each hold by *positivity* to allow for a proper gauge of difficulty. Further work will then begin on planning routes based on the holds found and their difficulty.

2 Acquisition Method

The part of the goal of this project is to be able to detect and classify holds on a wall in real time while at a climbing gym. For this reason, a method of capturing the wall in memory is needed. Common methods of acquiring this data can range from laser scanning to simply taking pictures. As a low cost solution for acquisition a single camera can be used and, from that, both two dimensional images and three dimension models could be generated.

2.1 2D Space

Two dimensional images are the easiest method of acquisition. A camera phone is a widely available tool that can be used for this. This method is excellent for rapid acquisition and can provide a large number of test sets for the project. It also allows for the use of stock images online. An example image can be seen in Figure 1.

This method, however, suffers from a number of drawbacks, mainly camera and lighting differences and lack of depth information. There can be a great deal of variance between an image taken by a camera phone and an image from a DSLR. If the detection algorithm is created to fit images taken on one camera,

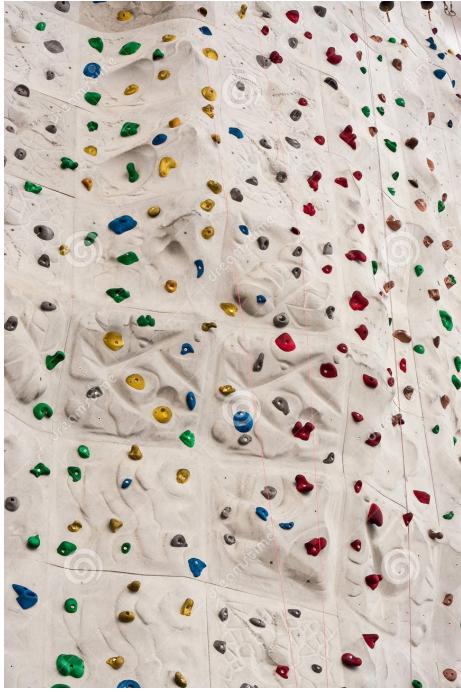


Figure 1: Stock image of a rock climbing wall.

there is risk of overfitting and poor results when a different camera is used. This method can also suffer from shadows and variance in lighting conditions. Both of these issues can be minimized by using a good quality camera in a climbing gym, where lighting conditions can be considered constant. Depth information can still be an issue, however. Some amount of depth can be found by taking a sequence of images, but holes inside holds and the top of holds that are high on the wall cannot be found.

2.2 3D Space

Three dimensional information is gained using photogrammetry. This is a method of creating a 3D model by stitching together 2D images. Autodesk Remake is used to complete this process. The result is a high resolution model that fully recreates the wall. An example portion can be seen in figures 2 and 3. This model gives full view inside and around each hold and preserves the angle of the wall relative to the ground. The example model is created from 250 images of the wall from several different views.

With this method, the main drawback is acquisition time. The current model only spans about 5% of the entire wall but required about 250 pictures and nearly an hour of computation time. The pictures can be taken relatively quickly, about one minute for the full set, but each set of 250 must be processed into a model individually due to the limit set by the free version of Autodesk ReMake. These models would then have to be concatenated together to build the full model.

Space complexity is also a consideration. The model shown has just over a



Figure 2: Right side view of wall model.



Figure 3: Top side view of wall model.

quarter million points, which could lead to unrealistic processing times. This can, however, be combated by decimating the model, that is, reducing the number of polygons used to represent the model. This experimentally is able to remove up to 80% of the points used, at the expense of resolution. The full wall, however would still have excess of a few million data points.

The final drawback of this method, which leads to the decision to continue in 2D space instead, is that the model itself is not a real-time model. It captures the wall from some point in time, but as new routes are set, the model becomes obsolete. Future work could explore the possibility of mapping new holds to a 3D model of the bare wall structure, instead of recreating the entire model each time. For this project however, 2D images will be used.

3 Hold Detection

One of the main aspects of this project is the ability to locate the holds found on a given rock wall. This allows the project to work on any wall without having prior knowledge of the wall or its holds. This also accounts for the rapidly changing nature of rock climbing walls. Most gyms will add new routes to their

wall on a weekly basis, making pre-mapped hold locations obsolete. An ideal hold detector finds the location and size of all holds within a given image.

3.1 Detection method

The following process is run on a single two dimensional image. The photo in Figure 1 will be used for example. First, a median filter is applied to the starting image. This removes some amount of noise from chalk and other impurities on the wall while preserving or even sharpening edges between holds and the wall. Then, openCV’s Canny Edge detector is applied, resulting in a binary image where only the edges remain. This detector works by finding the intensity gradient of the image, applying non-maximum suppression to get thin edges, and then thresholding the resulting edges between an upper and lower boundary. The last portion, the threshold, is subject to change in our process due to difference in lighting conditions and the style of the wall. Instead of using a fixed threshold, Otsu method is applied beforehand to find an optimal threshold for the image. The resulting image contains the edges of each hold with sufficient accuracy. From the edges, the contours of the image are found. Each contour defines a curve containing a set of continuous points or, in this case, the edges.

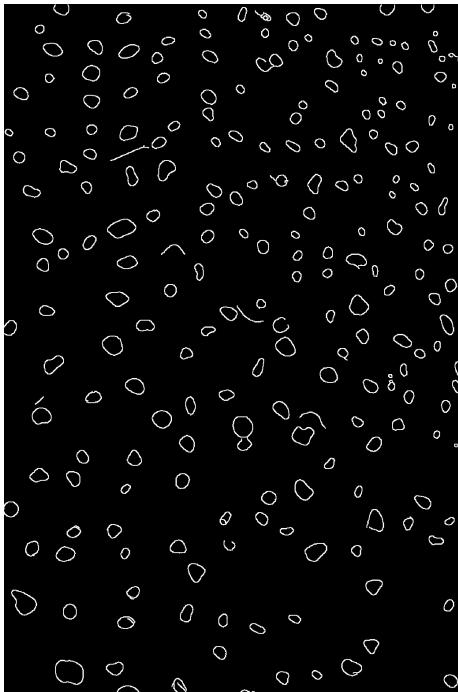


Figure 4: Contours of processed image.

Due to chalk residue, lighting issues, etc., these contours are occasionally missing some small portion of the full hold. To account for these gaps, a minimum spanning polygon, or convex hull, of each contour is used. From there, openCV’s blob detector can be used to identify each of these hull. Parameters are set so that blobs that are too small or have too low inertia are ignored. A



Figure 5: Full process of hold detection and classification.

list of keypoints are returned with position and size of each hold. This can be seen in Figure 5.

3.1.1 Drawbacks

There are some issues seen with this classification method. Shadows can occasionally be misclassified as holds and holds that have colors very similar to the wall can miss. This method also has no depth information, which means it can be hard to distinguish the type of the hold and therefore the difficulty. Two holds can be drastically different in complexity if one juts out of the wall and the other is nearly flush. Using a live video and tracking information about each hold could provide a valid solution to this issue.

4 Color Sorting

From the keypoints generated from the image, the color of each hold is determined. In most rock climbing gyms, the route on the wall is shown by colors. A set of yellow colored holds would mark a single route to the top. Each route has some rating of difficulty (Normally marked between V0 and V7, where V0 is the easiest). By finding the color of each hold, it can be associated with a route and some information can be gained about that difficulty of the hold can be gained.

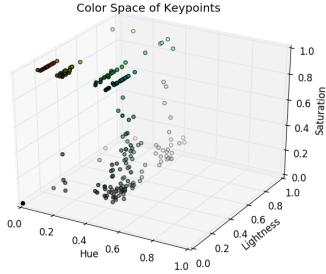


Figure 6: Plot of the color of each hold in HLS space. Apparent clusters can be seen, the red group, yellow group, green, etc. Using k-means clustering algorithm, these groups can be identified to find which route each hold belongs to.

4.1 Color identification

Because of difference in lighting conditions, color shades between holds, and chalk or other debris covering holds, color identification can be difficult. The image is first converted into the HLS colorspace to more heavily emphasize the difference in hues between routes. Then, for each keypoint identified by the hold detector, an image mask is generated. This mask marks a subsection of the image to consider. While the hold will take up most of this section, there are still portions of the wall and chalk cover in the image, making a mean color filter inaccurate. Instead, the pixels of each channel of the image is placed into a histogram, which shows the number of occurrences of each value. Each bin of the histogram is set to have a width of 4, meaning values 0-4, 5-8, and so on are grouped together. This effectively quantizes the image so that slightly different pixels are not considered different. The most common color is then returned from the resulting histogram and the channels recombined. The resulting colors can be seen plotted in HLS space with its original RGB color in the graph on Figure 6.

Bibliography <http://www.academypublisher.com/proc/isip09/papers/isip09p109.pdf>