Indoor Rock Climbing Wall Route Displayer

Eric Wei
Electrical Engineering, Stanford University
Stanford, California
ewei2@stanford.edu

***Abstract*—The soaring popularity of rock climbing stems from the challenge of conceiving and completing routes of increasing difficulty. Separate routes on the wall are often graded by difficulty, but fluctuations in this delineation exist for different facilities and thus a standardized system can provide a more accurate and enjoyable experience for climbers. This project takes an image taken of the climbing wall by an Android phone and overlays a directed route for the user to perform. This is accomplished through utilizing a scale-invariant feature transform descriptor matching algorithm to retrieve a preconfigured route combination from a crafted database. The results show error-free detection of the climbing wall can be achieved through utilization of 5000 homography trials.**

Keywords—scale-invariant feature transform; SIFT; random sample consensus; homography matching; template matching; color histogram; Android application;

I. Introduction

Indoor rock climbing has become an increasingly popular recreational activity, with more than 6 million people across the country participating in some form of climbing [1]. Once a place where only experienced climbers used to train in preparation for outdoor climbing, the indoor climbing gym is now home to individuals of all ages and skill seeking an enjoyable form of exercise. The appeal of rock climbing stems from both the physical task of scaling the wall as well as the mental challenge of discovering the correct path to take. Indoor climbing wall facilities often times delineate routes through a grading system that allow for climbers to undertake a natural progression of routes to complete as a means for measuring improvement over time. However, this grading system is highly subjective and can fluctuate widely throughout different climbing facilities. Thus, a climbing route mapper has the capability for providing an objective evaluation of routes that can provide climbers with more accurate and knowledgeable decisions when undergoing climbing routes. The ability to map an entire route tree can also increase the repeatability of routes for experienced climbers by introducing more difficult and undiscovered routes to accomplish. The production of a route displayer would greatly enhance the experience for climbers at the climbing gym.

This paper presents the methodology and results for the creation of an Android application designed to identify and display a preprogrammed route onto a captured photograph of the climbing wall using the camera's phone. A database is created using previously taken pictures of the climbing wall and segmented to form the template of each identified wall. The application then utilizes scale-invariant feature transform (SIFT) descriptor detection to identify the highest matching wall. Finally, the matching SIFT descriptors are utilized to map out the climbing route which is then displayed back onto the phone. The results from this project lay the foundation to the eventual forming of automatic identification and evaluation of climbing routes that can be displayed in real time.

II. Image Processing Algorithm

A. Overall Design

The process from taking an image of the climbing wall to displaying the image of the route tree requires a multitude of image processing steps on several fronts. Fig. 1. shows a representation of the different areas that are addressed within the scope of the project, which include the acquisition and presentation of the image, the creation of the database, and testing and implementation of the database using a captured image. Each area will be discussed in detail within the following sections. The summarized process involves creating a database of different wall templates and matching captured wall images through the use of identifying common SIFT keypoints. A designed route tree can then be established through designating keypoints as various steps for the route combination which is then formed and displayed back onto the Android phone.

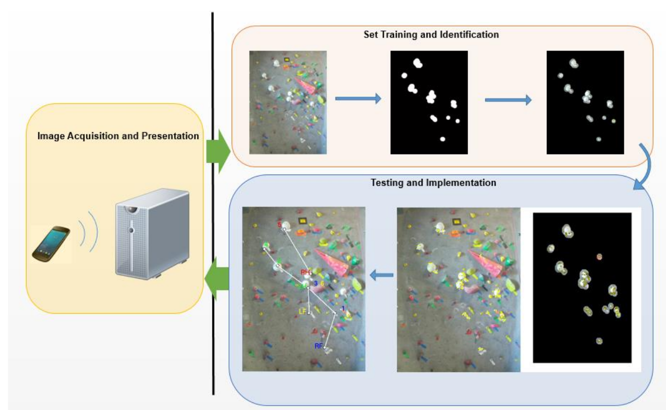

Fig. 1. Block diagram for overall process. The core components of the application can be delegated to three different areas: image acquisition and presentation on the client side, and set training and testing on the server side.

B. Image Acquisition and Presentation

The first step is to take the image captured by the camera of the Android phone and send it to a server for further processing. The Android application is coded in Java and possesses the capability of using the camera on the Android phone and reading a PHP script on the server side (SCIEN Lab Computer) to determine the state of the program in terms of image uploading and processing. After the server is done processing, the application then reads a flag that indicates for the image to be displayed on the phone. The processing scripts on the server are run through MATLAB.

C. Database Formation

Preparation of the wall database must be accomplished as a prior step before the application can be utilized. The database includes front-on pictures of the holds for the desired climbing route to then be able to obtain the SIFT keypoints for comparison. Thus it is imperative to undergo processing that will be able to focus upon the areas of the holds. Since each climbing route is determined by the distinct color of the holds, segmentation of the wall can be achieved through forming a binary mask that will only target a sub-band of colors. The means chosen to accomplish this is through the use of separating the regions of interest through examination and

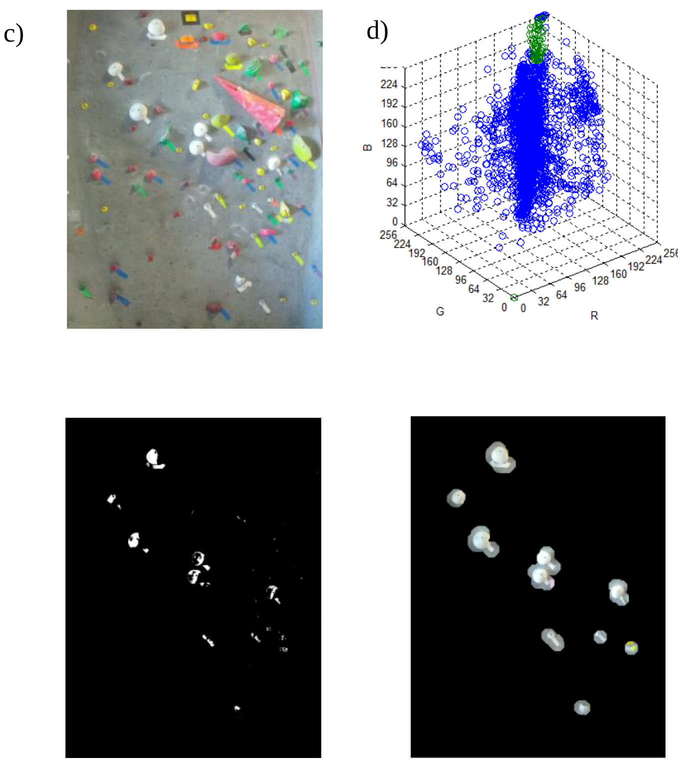

Fig. 2. Images processing for formation of database templates of different route configurations a) Image of climbing wall containing targeted holds (white) b) RGB histogram of a subsample (1/25) of the image. The green markers indicate targeted portions of the wall. c) Portion of image within the targeted color threshold. d) Cleaned binary mask applied to original image to form the complete template for the holds.

Fig. 3. Segmented wall of climbing holds using described process. Parameters used are R values between 200 and 256, G values between 0 and 100 values, B values between 0 and 100, no image erosion, image dilation using disk of size 30.

delineation of the color histogram of throughout the image [2]. Although the HSV color scale is often utilized for this process, RGB is chosen due to the greater degree of freedom for the range of colors that exist upon the climbing wall. Analysis of the RGB histogram of the image is used determine the necessary cut-off values of RGB values that must be obtained to form the binary mask for the template.

An example of this process is shown in Fig. 2. The original wall image is shown as well as the RGB histogram of a subsample of the image. Due to targeting of the white holds, the cluster of values within the histogram that are targeted includes the region of R values between 210 and 256, G values from 200 to 256, and B values from 200 to 256. The indicated points are shown in Fig. 2c. which indicate large portions of the holds as well as some areas of noise due to patches of the same color that exist throughout the image. To form the image mask, the points of noise are removed using image erosion. A disk of size 7 was found to be sufficient to remove the areas of noise from Fig. 2c., and the areas that remain are then applied an image dilation using a disk of size 50 to form the binary mask that is then used with the initial image to form the resulting template shown in Fig. 2d. A similar process can then be undergone to create a template for several climbing wall images to obtain the database for walls that can be implemented for recognition. This method is robust for holds of all different sizes and shapes as shown in Fig. 3.

D. Image Testing Implementation

After formation of the dataset, a testing algorithm must be implemented to match the captured image of the wall by the user to ones in the database. The choice for implementing a matching algorithm must be robust to several factors for effective utilization of multiple targets [3]. It also requires efficient matching against factors such as deformities and cracks on the wall [4], and a large field of view required to capture the entire climbing wall [5]. Thus a feature based image comparison method is used using SIFT keypoint matching [6] that is largely effective for different scalings of the image and fairly good against varying angles and illumination. SIFT keypoints are created through detecting local minima and maxima from applying scaled difference of Gaussian filters that identify the keypoints to form feature descriptors with information about the magnitude and direction of features around a subregion. For implementing a SIFT descriptor matching test, the SIFT keypoints of the templates within the database are found and then stored. Due to the lack of defined features for some of the holds, a peak

Fig. 4. Corresponding SIFT keypoints between the original image and the matching template within the database.

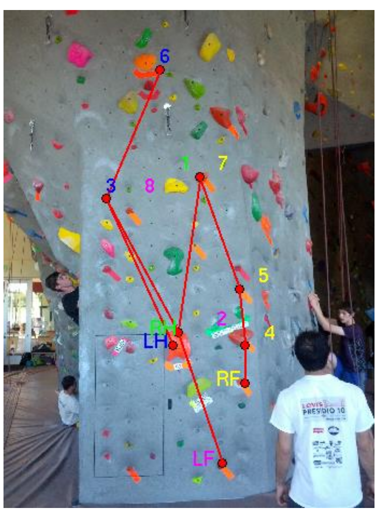

Fig. 5. Designation of predetermined route combination onto the matching wall using the original template image as the input.

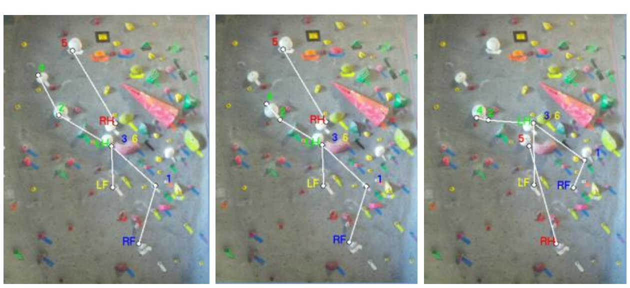

Fig. 6. Output image for climbing wall image taken by the created application for a) 5000 trials b) 2000 trials c) 500 trials for RANSAC. Utilization of fewer trials show increasing degrees of errors within the mapping.

threshold of .1 and edge threshold of 300 is used to form the necessary number of SIFT keypoints to be saved. SIFT descriptor matching with utilization of random sample consensus (RANSAC) using an affine model allows for the ability to accurately match up SIFT descriptor from the template image to the compared image as shown in Fig. 4. The RANSAC method takes a random subset of 4 correspondences and applies geometric mapping through linear regression to obtain the maximum number of inliers. It was found that matching the entire template rather than individual holds provided a higher success rate due to some holds possessing a low number of keypoints as well as the ability to distinguish between holds with similar shapes. The input image is tested against each database image to determine the highest number of inliers which refers to the matching template image. Due to the high repeatability for the designations of the SIFT descriptor matching, the formation of the preconfigured route is mapped directly onto the keypoints for the original image that designate the required instructions for completion of a route as shown in Fig. 5. Each database possesses the index of the matched SIFT descriptors, the label and order of instructions, and color for displaying the text and lines.

III. Results

The configured application and scripts were tested using a Samsung Galaxy Nexus phone running Android v4.3 against climbing wall routes at the indoor climbing gym at the Arrillaga Outdoor Education and Recreation Center (AOERC). The resulting product shows the correct choosing of the template image and the formation of the route combination onto the taken image by the Android phone that is successfully displayed. Through testing, it was discovered that the capability for producing error free images relied heavily upon the number of trials to form the homography of the geometric mapping for RANSAC. Fig. 6. shows the resulting image for various numbers of homography trials during the RANSAC process for determining the maximum number of inliers.

The relationship between the probability of success for the geometric mapping against the number of homography trials during RANSAC is given by

$$S = \log(1 - P)/ \log(1 - q^k) \qquad (1)$$

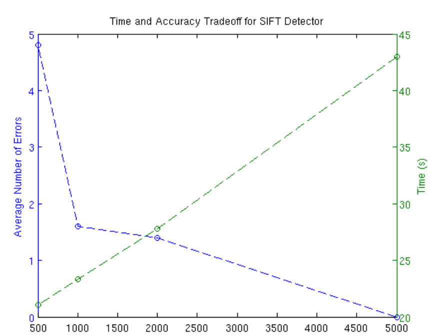

Fig. 7. Experimental results detailing the tradeoff between error-free operation of the application and time required for completion of the SIFT matching.

where P is the probability of success, q is the probability of valid correspondence, k is the number of correspondences per random subset, and S is the number of required trials. Thus for a small q, which is possible due to the lack of distinct feature descriptors in some areas, a large number of trials will be needed to have virtual error-free (> 99%) success. However, using an exorbitant amount of trials can lead to extended processing times that detract from usability of the application. This tradeoff is illustrated in Fig. 7, where it is shown that the number of errors can only be completely eliminated using upwards of 5000 homography trials. The consequence is that the time required for the completion of the SIFT matching algorithm increases linearly with the number of homography trials. Thus utilization of the SIFT keypoint matching detection can be used for high reliability, but at a cost of large operation times. This can be detrimental for mobile use as instant feedback is demanded by the user, and thus further investigation into reducing the computation time, such as using multiple servers or database-free identification, must be achieved.

IV. Conclusions and Future Work

The results show the successful implementation of the mapping and display of a preconfigured route on top of a user captured image of the rock climbing wall. Through the proper tuning of the number of trials during RANSAC, a virtual error-free route displayer is attained. Further work must be done to maintain the high accuracy without the cost of a long overheard time that prevent the utilization of presenting the results in real time. Utilization of a different keypoint matching algorithm can lead to higher reliability against different perspectives upon the wall. The results provide the first steps towardds the natural progression towards an automatic route evaluator.

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References

[1] E. Ailworth, “Number, popularity of rock gyms climbing,” *Boston Globe*, (2013).

[2] S. Sural, G. Qian, and S. Pramanik, "Segmentation and histogram generation using the HSV color space for image retrieval," presented at IEEE International Conference on Image Processing, Rochester, New York, (2002).

[3] H. Ammari, J. Garnier, H. Kang, M. Lim, K. Sølna, “Multistatic imaging of extended targets,” *SIAM J. Imaging Sci.* **5**, pp. 564–600 (2012).

[4] F. Graf , H. Kriegel and M. Weiler, "Robust segmentation of relevant regions in low depth of field images", *Proc. 18th IEEE Int. Conf. Image Process.*, pp. 2861–2864, (2011).

[5] M.R. Jahanshahi, S.F. Masri, C.W. Padgett, G.S. Sukhatme, “An innovative methodology for detection and quantification of cracks through incorporation of depth perception,” *Machine Vision and Applications*, pp. 1–15, (2011).

[6] B. Girod, “EE 368 Lecture Notes,” Stanford University EE 368: Digital Image Processing, (2014).