Hackulus Thriftus: A New Virtual Reality

Siena McFetridge (scm2539)
scmcfetridge@utexas.edu

Paige Hinkle (ph7457)
phinkle@utexas.edu

Jon Lee (cjl2443)
chencjlee@gmail.com

Jaime Rivera (rjr2426)
jaimerivera@utexas.edu

Rohan Ramchand (rsr898)
rohan@ramchand.me

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1 Overview

The goal of virtual reality is to immerse the user in a world that, although totally artificial, resembles the real world to a degree at which the user would be incapable of distinguishing simulation from reality. The goal of computer vision is to take real-world objects and situations, and translate it into terms a computer would recognize. While the goals of each of these fields often diverge wildly, there is one fundamental goal these two worlds share: to virtualize, so to speak, reality.

Our project therefore attempts to bridge these worlds in a novel way. Existing works have demonstrated that is possible to record the real world in a way that a computer might be able to recreate it; it is only fitting that these recreations might serve as a model for the degree of accuracy virtual reality hopes to emulate. To that end, the goal of the Hackulus Thriftus project is to combine the model of reality a Kinect is capable of recording with the model of reality Google Cardboard is capable of producing.

We demonstrate a novel usage of existing mathematical techniques for capturing a 3D model from stereoscopic camera data. We further demonstrate an application of this data to the model of virtual reality in Google Cardboard. We conclude with some general remarks about the results (and quality thereof) of our project.

1.1 Objectives and Key Results

We divided the project into three objectives, categorized alongside key results expected by the completion of each objective (OKRs):

Objective 1 Completion of the mapping of Kinect depth maps to point clouds for rotated objects

Objective 2 Completion of the mapping of Kinect depth maps to point clouds for scenes, where the Kinect is instead rotated

Objective 3 Completion of the translation protocol between point clouds and viewable scenes in Google Cardboard

2 Background

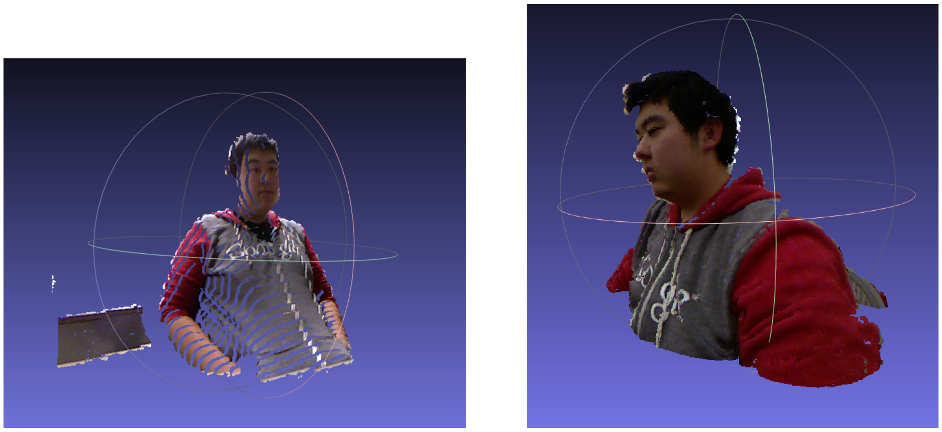
Three-dimensional object reconstruction is a cutting edge area of computer vision, and is currently being actively researched and developed for consumer use. The Kinect, an accessory to Microsoft's popular Xbox 360 gaming console, is a significant step forward in consumer-accessible 3D reconstruction hardware, as it mimics the functionality of cutting-edge research technology. Research has already been undertaken by Microsoft in the area of scene creation, resulting in a proprietary library called Kinect Fusion (which has an open-source counterpart, KinFu). Although we considered using these libraries, OpenCV proved to be sufficient for the creation of 3D meshes.

Virtual reality has long been an active area of research and is now a popular area of consumer technology as well, made accessible by the Oculus Rift and Google Cardboard. The applications for virtual reality remain as of yet untapped, but virtual reality most usefully allows for immersion into 3D spaces. Cutting-edge technology in the virtual reality space includes modeling and interaction with 3D objects and consumer products, such as in video games and interactive scenes. Google Cardboard, in particular, allows for a web-facing client that is powered by WebGL, a Javascript graphics library, through three.js, a Javascript mesh loader.

3 Methods

3.1 Kinect

The Kinect is a motion sensing input device made by Microsoft for their line of gaming consoles, the Xbox. It is a combination of 3 parts: a regular color camera, an IR camera,



(a) Point-Cloud Capture

(b) Different Angle

and an IR projector. From our basic understanding, the IR projector projects a known speckle pattern which the IR camera picks up on and can calculate depth by figuring out the spacing of the speckles. We chose the Kinect as our method of scanning objects because of the accuracy of the depth maps produced, and because one was readily available and was well-supported in OpenCV.

Using the OpenNI library, PrimeSense's NiTE middleware, and SensorKinect library, we were able to connect to the Kinect successfully through OpenCV. Initially, we grabbed the disparity image and the BGR image for each frame from the Kinect, which we ran through Project 2's disparity-to-point cloud generator. This produced the results seen in our second progress report. Ultimately, we felt that the point clouds generated in this fashion were not very detailed, in that the depths were discontinuous. In searching for a better method, we found that we could get the raw depth map from the Kinect in millimeters from each pixel. Combining this with the BGR information from the color camera, we were able to generate a much better point cloud, as seen above.

Since we were now able to construct detailed 3-dimensional point clouds from the Kinect, the next objective to tackle was to properly transform different point clouds onto one another. To simplify the problem, we believed that a single object on a lazy susan would be ideal, since we would only need to solve for the center of rotation and rotation matrix. We took each image from the Kinect and found corresponding features between the images. These were the points within the point cloud that we used to find the optimal rotation. We toyed with the idea of using a clever ternary search algorithm to eliminate having to manually rotate the object by specific degrees.

However, as this approach would have made an unreasonable amount of assumptions about the environment, we decided to fea-

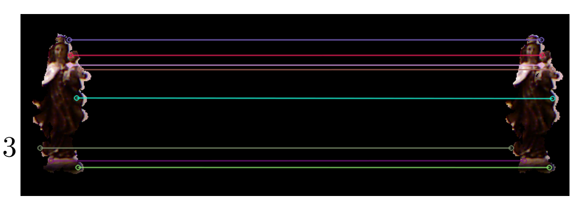


Figure 2: Feature Matching in OpenCV

ture match as usual, but to use Singular Value Decomposition (SVD) to find the rigid transform between the two point clouds; in particular, we relied primarily on the SVD implementation supplied by OpenCV. The main issue was therefore reduced to proper feature matching between the images. We found features using SURF, created descriptors from SIFT, and finally matched using a brute force matcher. To reject further points, we made the assumption that our rotation was along the y-axis, which simplified the problem without making unreasonable or incorrect assumptions. The issue remains that the Kinect base needs to be perpendicular to the axis of rotation of the object. We believe this approach should work fairly well, but we were unable to properly apply our matrix transformations.

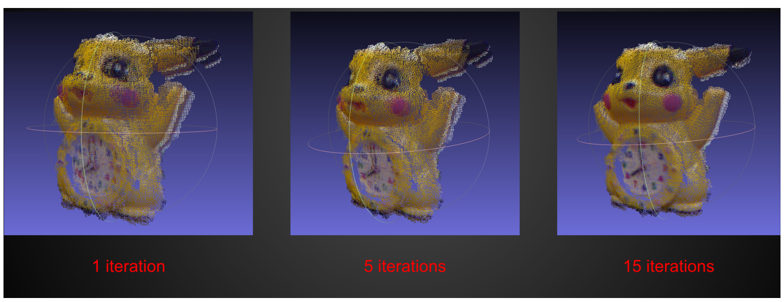


Figure 3: Quality over Iterations

Frustrated, we started working on a new implementation of our current work, this time more carefully implementing the interactions with OpenCV's Mat matrix format. In the process, we also decided to fully implement Iterative Closest Point (ICP). ICP is one of the current industry standards for point cloud registration. The way it works is by finding the nearest neighbor in the registered points for each point to be registered and calculating an optimal transformation matrix to transform the points to their neighbors that minimizes error. After transforming the registrant points, the process is repeated again, multiple times, with each iteration getting closer and closer to a good match. ICP requires a set of correspondences, much like our previous implementation. This time we opted out of using the feature detection to find correspondences because of small issues we had, and instead took the entire point cloud union as we iterated and found the closest points, using OpenCV's Flann index KD tree, to the new point cloud to be registered, as our correspondent points. Due to the nature of ICP, implementations usually require some initial guess of the spatial orientation of the point cloud to be registered. To avoid using an algorithm like PCA, we instead rotated the entire union of point clouds registered so far, so that the point cloud to be registered and the union of point clouds were fairly close to start off with from the view of the Kinects frames.

This approach ran very slowly, but we were able to overcome this by instead accumulating the rotation and translation matrices from previous registrations and applying that to the registrant point cloud. We then further optimized the registration process, by using a random sampling of points between each frame, and using those for the initial set of correspondences, instead of the entire point cloud. This increased efficiency by an order of magnitude, and allowed us to generate significantly larger sets using many more points. We believe that employing feature matching into the picture to have an initial set of correspondences that are closer than the rotation of the entire point cloud would also positively affect efficiency, but we did not further explore the idea.

3.2 Cardboard

We decided to use Google Cardboard for our virtual reality viewer because the learning curve is significantly shallower than the more complicated Oculus Rift. Instead of Unity, the framework that powers the Rift, Cardboard supports a JavaScript-based web application or an Android application. We chose to make a web application to view our 3D scans created using the Kinect.

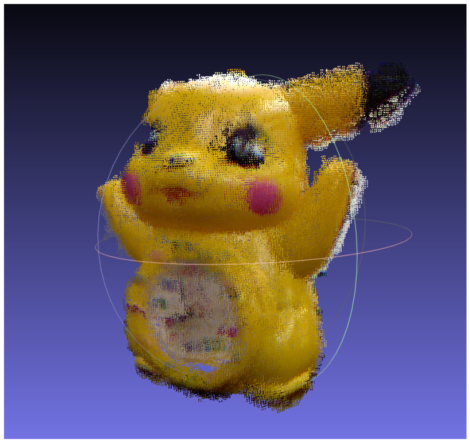
The harness for the initial setup is supplied by Google for developers. It splits the screen in half with a slight offset to create the optical 3D illusion. This is created using Javascript, WebGL and three.js. Making a virtual reality scene does not differ from creating a 3D graphic scene after splitting the views, and so therefore to create the scene, we added a modified camera, additional lighting, and a 3D representation of our Kinect scans. This 3D object was created by loading in our scan and converting it into a WebGL object.

We decided to create an object (.obj) file from the 3D scans we were expecting as output from the Kinect to make loading the imagery into Cardboard via three.js simple, as open-source loaders already existed. However, we instead were forced to write a point cloud (.ply) loader from scratch, as no open-source alternative existed for JavaScript. This involved parsing each line in the file, which contained a point's coordinates and RGB values. The points required some fine tuning to suit the three.js format, and then were added to a Geometry object which contained all the points. The RGB values were saved in a Color object, and then associated with the Geometry object at the end. This could then be converted to an object and material which could then be added to the scene.

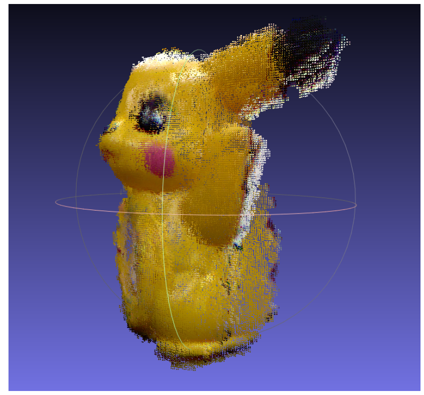
4 Results

4.1 Kinect

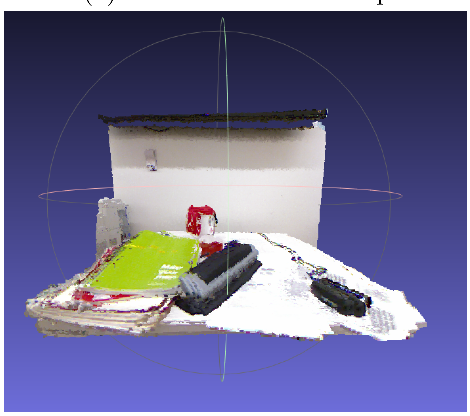
For the Kinect portion of the project, we initially set two major goals: to recreate a 3D object by moving an object in front of the Kinect and to recreate a 3D scene by moving the



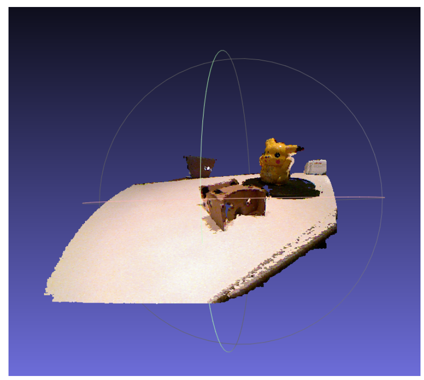
(a) Final Point-Cloud Capture



(b) Different Angle



(c) Final Point-Cloud Capture



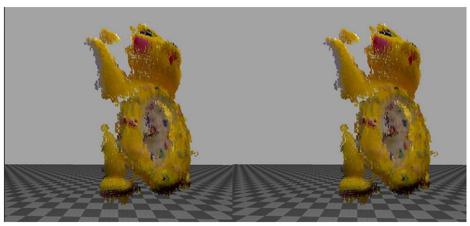
(d) Different Angle

Kinect. We were able to complete both goals by re-creating both a Pikachu alarm clock and by re-creating the table next to the GDC 3rd Floor Lab Printer.

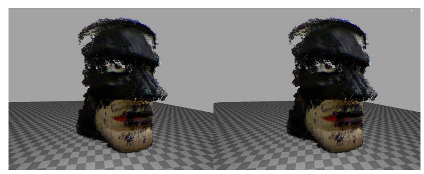
While we achieved the intent of both our original goals, we did not fully complete them, due to irrelevance of the initial goal or due to technical difficulties. Our original goal for scanning a scene using a rotating Kinect became irrelevant because we were able to scan a scene by fully moving the Kinect around. On the other hand, because of the complexity we didn't expect in implementing the point cloud registration algorithm, we decided to put creating meshes out of our point clouds on the back burner. This ended up not being detrimental to the spirit of our project though, because we were able to implement viewing of point clouds in Cardboard.

There were also some limitations to our solutions. Our current implementation is unable to generate a full 360-degree model of an object, often times failing after about a 90-120 degree rotation; we believe this is due to a bug in our implementation with the computation of the rotation matrix, specific to OpenCV. Our implementation also fails to generate 3D models of objects that are perfectly round, in that the rotation of the object produces no change in the depth of what is visible to the Kinect (this is due to the fact that we are not doing any estimation of the pose of the Kinect). We proposed introducing the BGR values in the computation for finding the closest neighbors in order to force a rotation in objects that have color texture but no depth texture, but did not have time to fully explore this idea. Given more time, we would like to see whether any of our proposals can solve the problem.

4.2 Cardboard



(a) Pikachu Render



(b) Batman Render

We initially set two goals for this section of the project. We primarily wanted to view one of our 3D scans in the web app we created for Cardboard. We set as an additional goal the ability to view the object from multiple viewpoints. We were able to complete the first goal by being able to view our own PLY files in the space, as demonstrated in the image.

However, we were not able to complete the rotation segment of our goals. Originally when we were using OBJ files, this process was not difficult, as we could rotate the entire object together. We were even able to rotate the object using the device's pitch and yaw to integrate the virtual reality space better. However, when we converted to PLY, this became much more difficult as we would be rotating the individual points. Thus, we did not continue to rotate the object and instead allowed the user to rotate in the scene, where the object was stationary. At any rate, this proved an insignificant hindrance, as our 3D reconstruction only extended to the front 180 degrees of the object, and therefore the ability to see the back of the object became unnecessary.