Project PAALM: Phalangeal Angle Approximation through the Leap Motion Controller

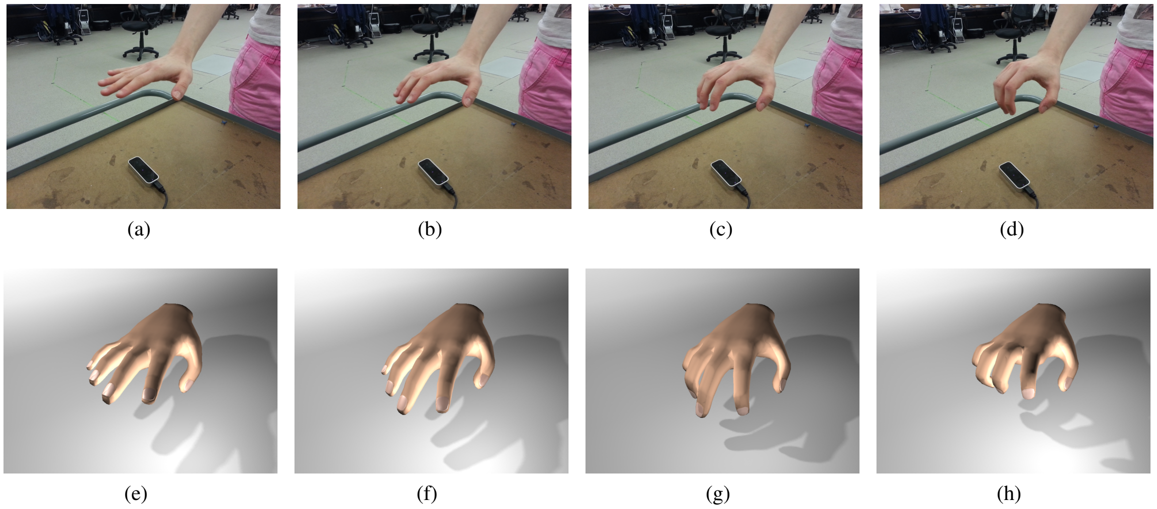


Figure 1: *Top Left to Right: The Leap Motion controller tracks to palm and fingers above it. Bottom Left to Right: Our PAALM system estimates finger positions in real-time based on the Leap input. The bottom animation was created using a Maya plugin which communicates directly with the device to create keyframes for a hand model.*

Abstract

Hands are fundamental in a variety of domains including character animation, sign language, robotics, and gestural user interfaces. However, the dexterity and flexibility of the hand make it difficult to accurately capture information about complex gestures. Current approaches are expensive, restrict movement of the hand, confine the user to a capture region, or require time-consuming manual cleanup. Thus, we investigate the use of a fast, approximate, and inexpensive method for obtaining the phalangeal joint angles of the hand using the Leap Motion Controller [Leap Motion 2013]. Our framework directly integrates the Leap Motion controller into Maya to create an intuitive user interface for animating hand motions.

CR Categories: I.3.3 [Computer Graphics]: Three-Dimensional Graphics and Realism I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism;

Keywords: user interfaces,motion capture,hand animation

1 Introduction

Hands are fundamental in a variety of domains including character animation, sign language, robotics, and gestural user interfaces. Hands are both the primary mechanism we use to interface with the physical world as well as an important component for communication. In computer graphics, the realistic animation of the human hand is a long-standing and difficult problem because our hands are very dexterous and versatile. Detailed and subtle finger motions are important for lifelike characters but are difficult to capture. Much research has been devoted to efficiently capturing hand gestures, using imaged-based, glove-based, and marker-based techniques. However, most existing methods remain expensive, can restrict the motion of the hand, might confine the user to a space, or require time-consuming manual cleanup. For example, dexterous finger motions are very difficult to capture with optical and marker-based systems because markers frequently become occluded and the proximity of the fingers cause automatic labeling algorithms to frequently mislabel markers. Conversely, solutions involving wearable measurement devices, such as cybergloves, are often bulky and restrict delicate movements.

We use the data from the Leap controller to estimate the phalangeal joint angles of the fingers and palm. Thus, we investigate an effective method for approximating and recording hand motions that is portable, unrestrictive, real-time and cost-effective. Our approach utilizes a new and unexplored technology called the Leap Motion Controller that is roughly the size of a flash drive and tracks individual finger movements to 1/100th of a millimeter [Leap Motion 2013]. This device is designed to sit on a desk and plugged into a PC via USB. Internally, the device tracks finger motions in a one meter hemispherical area above the device using two light sensors and three infrared LEDs [(https://www.leapmotion.com/developers)].

Our framework implements an application programming interface (API) for obtaining and visualizing the phalangeal joint angle data using the Leap Motion Controller which is suitable for direct import (via a plug-in) into a rigged Maya hand model. Unlike a purely image-based system, the Leap Motion device provides users with direction vectors and lengths for each finger as well as an orientation and position for the palm. We map the output from the Leap Motion controller to IK targets for each finger based on a simple calibration step.

Our main contributions are as follows:

- An portable, cost-effective, real-time, and freehand method of obtaining phalangeal joint angles using an unexplored technology.

- An application programming interface (API) for obtaining and visualizing the phalangeal joint angle data using the Leap Motion Controller which is suitable for direct import (via a plug-in) into a rigged Maya hand model.

2 Related Work

Recording hands remains a difficult problem. Below we briefly outline four major approaches.

2.1 Marker-based Systems

Marker-based motion capture systems are a popular means of obtaining hand motion data. The standard approach requires attaching approximately 30 retro-reflective markers to the hand and tracking them over time [Vicon 2013]. The temporal data is then used to reconstruct a 3D representation of the hand and its motions. Recent advancements in hand motion capture have made it possible to achieve descriptive hand motion data with a reduction in the number of markers [Hovet et al. 2012]. Though even with such advancements, marker-based approaches still pose significant problems in hand motion detection. Gestures featuring self-occlusion (fingers overlapping one another) are difficult to detect using the system. Automatic marker tracking is not effective in maintaining the markers over time. Thus, the process of tracking markers is then a tedious one, requiring manual labeling that is both time-consuming and error prone [Zhao et al. 2012].

2.2 Glove-based Systems

Glove-based systems such as the CyberGlove [Cyberglove 2013] provide a useful method of obtaining hand gesture data that is free from issues that arise when fingers occlude each other. Such systems have been used for the recognition of sign language [Vogler and Metaxas 2003]. The motions recorded using the system, however, are often noisy and fail to capture delicate articulations with high precision [Zhao et al. 2012]. Likewise, the system restricts the natural motion of the hand, making capturing realistic gestures a more complex task. The advantage of using the Leap Motion Controller for our approach is that it permits the hand to move freely and naturally.

2.3 Image-based Systems

Computer vision has offered a promising alternative to data gloves and other worn mechanisms for detecting hand motions [Erol et al. 2007]. Image-based systems have the advantage of being lower cost, portal, and not restrictive of hand movements.

Image-based approaches must handle occlusions between fingers. [Martin de La Gorce 2011] tracked hand poses based on monocular video using a model of temporal continuity to handle occlusions. Other image-based techniques rely on hand motion priors stored in a large database to aid capture [Wu et al. 2001; Zhou and Huang 2003; Wang and Popovic 2009; Romero et al. 2010]. However, these approaches rely on having a large hand database to guide pose recognition and generation and thus have the drawbacks of requiring a large number of pre-collected poses and thus whose recognition is restricted to poses similar to those in the database. In an other approach, [Oikonomidis et al. 2011] enhanced the accuracy of imaged-based techniques through the use of a RGB-depth camera. A recent device called Digits has been developed that uses a wrist-worn gloveless sensor to detect 3D hand gestures [Kim et al. 2012]. The sensor features two infrared illumination schemes that are used to produce a hand model through inverse kinematics. The wrist-worn device avoids the need for any embedded sensors in the environment and permits the hand to move freely as well as the user to move about without being confined to a capturing region.

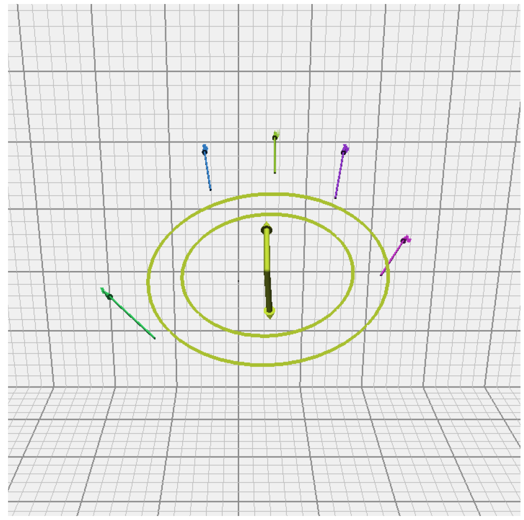
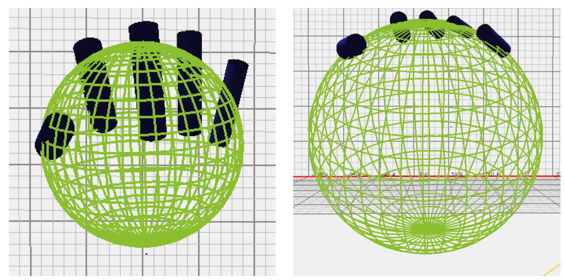


Figure 2: *Leap Motion visualizer displaying finger vectors and a palm normal for a hand.*



(a) (b)

Figure 3: *Top to Bottom: Leap Motion visualizer displaying the palm radius for a partially closed hand and an open hand with spread fingers.*

Vision-based techniques have the drawbacks of being computationally expensive, noisy and vunerable to a lack of obvious features on the hand and occlusions.

2.4 Hybrid Systems

A recent innovation has been combining marker-based and image-based systems to provide higher fidelity hand motion data [Zhao et al. 2012]. These systems are capable of accurately detecting hand motions even in cases of selfocclusion. The markers are used as reference when rebuilding hand motion data using an RGB-depth camera such as the Microsoft Kinect. These systems are robust and do not significantly restrict hand movements as the markers are small. The potential shortcomings of this system is that it still requires an expensive, non-portable optical motion capture system to capture the markers and must run a computationally expensive optimization to solve for hand positions which saistify both the RGB-D image and the marker positions.

3 LEAP

The Leap Motion Controller offers a cost-effective, fast and precise means of capturing live hand motion data. This device is small (3x1x0.5 inches), designed to sit on a desk and plugged into a PC via USB. Thus, it is extremely portable and lightweight.

The Leap Motion Controller is an infrared-based device, featuring three infrared LEDs and two light sensors. The device is capable

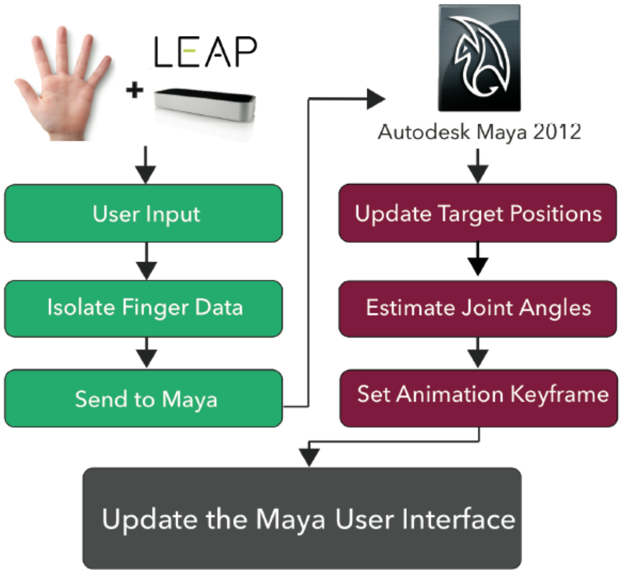


Figure 4: *PAALM Overview. To isloate finger data, we sort detected fingers by x-ccordinate and compute a ratio for estimating the amount of bend in the finger. This data is sent to a Maya plugin via a socket, occurring through Maya's command port. We then compute IK target positions by computing an offset for the finger tip based on a direction vector offset from the first knuckle joint of each finger. Finally, we set keyframes which may then be rendered out or exported to a motion file format.*

of tracking position changes as small as a 1/100th of a millimeter within a detection region of eight cubic feet. Its sensors capture spatial information at 290 frames per second and provide data about the tip position, tip velocity, length, direction, and width of pointable objects, such as a pen or a finger, in 3D space.

With respect to fingers, the device can determine to which hand a set of fingers belong and provide details about a hand's palm position and normal (Figure 2). Additionally, the hand data includes a palm sphere radius, or the radius of a spherical object that could be held within the palm of the hand. A small radius suggests a closed hand while a large radius suggests an open hand with fingers spread further apart (Figure 3). Occluded fingers are not detected by the device, so crossed or folded fingers will disappear from the output data until they are detected again.

All of the data provided by the Leap Motion Controller is organized into individual frames which can be accessed and manipulated using the device's application programming interface.

4 Approach

In this section, we describe how we map the output from the Leap device to a joint hierachy in Maya. The device API provides unordered direction vectors whose lengths correspond to the length of each finger seen by the device. The device omits information for any fingers it fails to detect, such as fingers folded into the palm or crossed together. The size, position, and orientation of the palm is also provided by the Leap API.

Thus, inferring hand positions from the Leap input requires mapping these direction vectors to the finger and palm of our model.

For this straighforward approach to work, we must first calibrate our system for the finger sizes of the capture subject, which can differ greatly between individuals. During this step, our capture subject need only hold their hand above the leap device in a rest pose with open palm and spread fingers, such that the device can detect the entire hand. We then record lengths of each finger over 1000 frames (approximately 10 seconds) and use the average as the standard length ℓ_s for the finger. The standard length is then compared against the current length ℓ_c in all subsequently captured frames to compute a length ratio $\frac{\ell_c}{\ell_s}$.

In Maya, we define joint chains for each finger apriori (which we will designate as Maya-fingers) having joint limits and sensible degree of freedom constraints. The leap direction vectors d are then scaled based on the length of each Maya-finger ℓ_m and the leap finger ratio to compute an offset from first knuckle of each Maya finger.

$$x_{ik} = \ell_m \frac{\ell_c}{\ell_s} \frac{d}{||d||} + x_{knuckle}$$

where x_{ik} is the global position for placing our IK target and $x_{knuckle}$ is the global position of the knuckle. Each frames, we then update the finger positions based on IK. Each N frames, we additionally save out a keyframe, with N chosen to based on the desired framework of the animation. These keyframes can either be rendered out as is, or exported to a standard motion format, such as amc/asf, v/vsk, or bvh.

Lastly, we must account for two complicating factors: one, the finger data for a hand received from the Leap Motion Controller is not guaranteed to be ordered; and two, some number of fingers might not be detected at all. The first problem is solved with a heuristic where we sort the finger data by x-coordinates in 3D space (chosen because it matches the orientation of a detected hand in the device's coordinate space). In our demos, we us ethe right hand although the system is suitable for either hand or can support two hands if they are not stacked on top of each other. The configuration need only be specified during calibration. The sorted fingers receive unique identifiers that are used to associate standard lengths (acquired during calibration) with lengths from subsequent frame updates. We deal with the second problem using heuristics to infer the missing finger, e.g. we assume that a finger will stay in the same position until it is detected again.

Our implementation has two main components: a Python script for interfacing with the Leap Motion Controller and a Maya plug-in written in PyMel for animating hand motions. The integration between the Leap controller and our Maya plug-in is socket-based, occurring through Maya's command port.

5 Conclusion

This work describes a simple, straight forward mapping of the leap device for estimating hand poses. Our framework directly integrates the Leap Motion controller into Maya to create an intuitive user interface for animating hand motions, but could be used as well as for puppeteering other rigged models. Once animated, the poses are easily exported from maya into standard motion formats such as amc/asf, v/vsk, or bvh.

The Leap Motion controller shows much promise for the collection of hand gestures, thanks to its small size, cost, and input capabilities which are tuned to the detection of hands.

The downsides of our current implementation is that it does not deal with the small levels of noise which are sometimes generated by the device, nor do we yet handle enough postures robustly. Lastly, we do not evaluate sophisticated methods for dealing with missing finger data or handling a wide variety of poses. This is the natural next step. However, even our simple approach produces compelling and intriguing results. Our hope is that this work encourages and aids others interested in trying this device.

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