Towards comprehensive capture of human grasping and manipulation skills

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Abstract- Grasping plays a central role in our daily life. To interact with objects surrounding them, people use a large diversity of hand configurations in combination with forces ranging from the small ones involved in manipulating a pen for writing, to larger forces such as when drinking a cup full of water, and even larger ones such as when wielding a hammer. In this paper we present a setup to capture human hand configuration and motion as well as the forces applied by the hand on objects while performing a task. Hand configuration is obtained through the use of a data glove device while interaction forces are measured through an array of tactile sensors. Current approaches in the state-of-the-art are limited in that they only measure interaction forces on the fingers or the palm, ignoring the important role of the sides of the fingers in achieving a grasp/manipulation task. We propose a new setup for a "sensorized" data glove to address these limitations and through which a more complete picture of human hand response in grasping and manipulation can be obtained. This setup was successfully tested on five subjects performing a variety of different tasks.

Keywords- human grasp response, human hand tracking, hand kinematics, tactile sensors

1. INTRODUCTION

Capturing and analyzing human hand motion is essential for several applications in fields such as robotic tele-manipulation where a mapping is needed in order to use the motion of a human hand to control the motion of a dexterous robotic hand [4], or in the field of immersive virtual reality (VR) [6] or VR-hand rehabilitation [5] where a user can grasp and manipulate virtual objects after mapping the user's hand motion to the motion of a virtual hand, or in the biomechanical field where one needs to measure and understand the mechanics of human manipulation in order to transfer these skills to robotic/prosthetic hands [1].

Vision-based methods have been proposed in the literature for manually classifying static human hand configurations [1, 3], or tracking hand motions [8]. Other hand tracking methods rely on data glove devices [4-6]. However, all these methods focus only on recording the hand joint angles ignoring the interaction forces between the hand and the manipulated object. Recently, the authors in [7] propose to cover the inner part of the hand with tactile sensors in order to quantify these interaction forces. This work is relevant for tasks such as holding a bottle or pick and place tasks. When dealing with many other tasks such as using a screw-driver or opening a tightly screwed bottle cap, the opposition of thumb surfaces against the sides of the fingers plays an important role [11] in applying the right amount of force and torque for successfully accomplishing the task. In other tasks such as writing or engraving/sculpting, this side opposition is essential for sufficient power coupled with fine control at the tool tip.

In order to capture side opposition one must employ tactile sensors on the sides of the fingers to measure the tactile response. But how this contributes to the overall grasp depends very much on the position and the orientation of the thumb grasping surfaces relative to the finger sides. As will be explained later, the thumb sensors of the Cyberglove exhibit nonlinearities which are difficult to model and several methods have been proposed to tackle this. When the application is fine tele-manipulation [4, 9], calibration stresses the 3D position accuracy of the finger-tips. Others [10] propose a calibration procedure focused on imitating the demonstrated hand posture as a whole. To the best of our knowledge there is no existing calibration method that has reported on capturing correct orientation of grasping surfaces especially that of the thumb vis-à-vis its opposition to the sides of the fingers.

We address these limitations in our proposed setup through two novel contributions involving the glove design and glove calibration. The rest of the document is organized as follows. Section 2 describes the construction of the "sensorized" data glove. Section 3 outlines our hand kinematic model and describes a new calibration procedure which focuses both on position and orientation of grasping surfaces. Section 4 shows the grasp response obtained using this infrastructure. Section 5 concludes the paper.

2. DATA GLOVE CONSTRUCTION

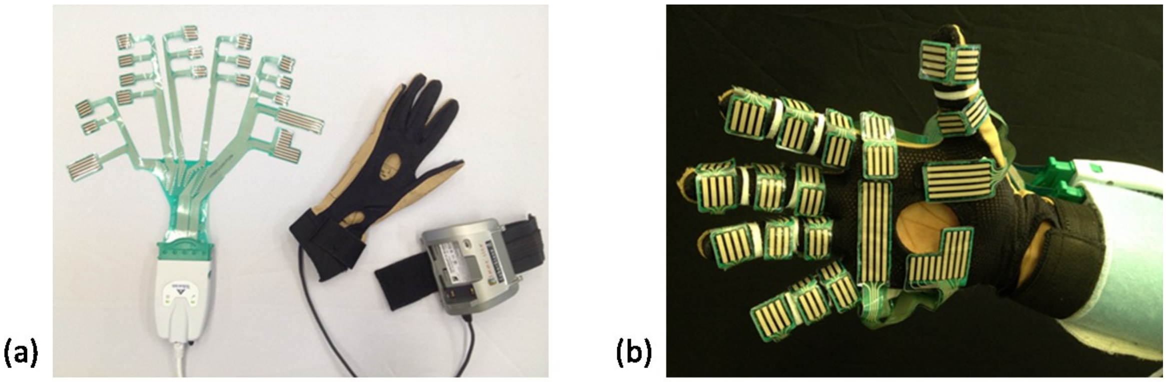

Figure 1. The Cyberglove data glove combined with 2 Tekscan tactile sensor arrays to form a “sensorized” glove for measuring human grasp response.

The main components of our setup are illustrated in Figure 1(a) and comprise of the Cyberglove, used to measure hand joint angles, and the Tekscan sensor array, used to measure the tactile response from the grasping surfaces of the hand.

The Cyberglove has 22 bend sensors strategically located over the hand joints. Since bending can be detected anywhere along the sensor length, the glove can adapt well to different hands sizes. The glove needs to be calibrated in order to transform raw sensor output to hand joint angles.

The Tekscan sensor array consists of 18 sensors patches which are matrices of pressure sensitive sensing elements or sensels. As can be seen in the figure, the patches in one array are strategically located so as to cover the grasping surfaces of the human hand. We employ two such tactile arrays in an overlapping configuration in order to cover the frontal grasping surfaces of the hand as well as the sides of the fingers. The Tekscan software provides methods for calibration whereby the raw sensor information can be converted to absolute force units.

The final “sensorized” glove can be seen in Figure 1(b). We synchronize the two data streams in order to analyze the tactile response along with the grasping configuration. The combined data is obtained at a frequency of 200Hz.

3. HAND KINEMATIC MODEL AND CALIBRATION

We are interested in capturing human hand posture. The first requirement is to build a hand kinematic model which is able to achieve most of the human hand postures, and which can be customized to accommodate hands of different sizes. The second requirement is to calibrate the glove sensors to the hand joints as they are defined in the kinematic model.

Kinematic Model

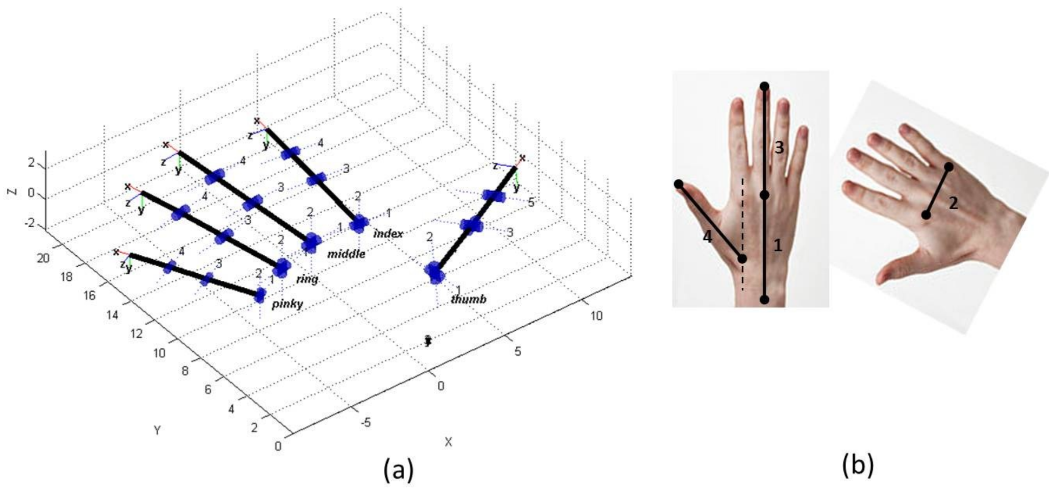

Figure 2. Kinematic model of the hand along with the 4 hand measurements for its customization

As shown in Figure 2(a), we model each finger as a separate kinematic chain which is positioned with respect to a coordinate frame located at the wrist. Following a common approach in the modeling of finger kinematics

[4, 9], we model the fingers with 4 revolute joints: 2 joints at the metacarpophalangeal junction (MPJ) for flexion and abduction and one joint each at the proximal and distal interphalangeal (IJ) junctions.

Modeling the thumb [9] requires 5 joints as it exhibits the ability for pronation/supination at the MPJ which needs to be taken into account for accurate positioning. Furthermore, this twisting motion of the thumb is not controllable but is a function of the flexion and abduction angle at the carpometacarpal junction (CMJ). Modeling this twist becomes even more essential when one is interested in the degree to which the grasping surfaces of the thumb are in opposition to those of the fingers. While thumb-twist has been modeled [4, 9] by a revolute joint with axis along the thumb metacarpal, we choose to locate this at the proximal interphalangeal junction with axis along the proximal phalanx. This is because the thumb-twist effect most influences the orientation of the proximal and distal grasping surfaces.

This kinematic model is determined by the link lengths and the location of the base of each chain with respect to the origin. These are set to default values corresponding to an average sized human hand provided by Cyberglove. We customize the kinematic model for each human demonstrator using 4 measurements of the subject's hand, Figure 2(b), to scale the default values. Grasping surfaces of the palm are not controllable in this model. They lie in the plane of the wrist at predetermined locations which also get scaled appropriately according to the hand measurements.

Calibrating the Cyberglove

Calibration of the fingers (index, middle, ring, pinky), is done by asking the subject to randomly explore the workspace of the finger joints by moving them between the opened and closed positions. Maximal and minimal joint values are recorded and subsequently mapped to the joint limits of a normal human hand. This method is feasible as the glove sensors vary linearly with respect to the finger joint angles. Thumb calibration is a bigger challenge because there is no sensor embedded in the glove for measuring thumb-twist, and there exists a coupling between the MPJ flexion and abduction sensors which depends on the hand configuration. Using a linear combination of the abduction and flexion angles to approximate the thumb-twist, [4, 9] observe good positional accuracy of the thumb finger-tip, but no result on the orientation was reported.

To calibrate the thumb we use a data-driven approach to model the non-linear relationship between the 4 sensors of the glove and the 5 joint angles of the kinematic model. The subject moves the thumb tip in a series of moves designed to completely explore the workspace of the thumb. During this procedure, we track the position and orientation of the thumb tip with respect to the wrist through appropriately placed markers and the Optitrack vision system. Next, for each position and orientation measured, an inverse kinematic solution is found by minimizing the position and orientation error between the observation and the 6D pose of the thumb-tip predicted by the forward kinematic model. Gaussian mixture regression is then used to model the relationship between the corresponding input (glove sensors) and output (joint angles) sets obtained. Regression parameters are obtained through cross-validation on the training set. We obtain a test set error of 0.71 cm in position with a standard deviation of 0.475 cm and 6.62 degrees in orientation with a standard deviation of 4.84 degrees.

4. HAND CONFIGURATION WITH TACTILE RESPONSE

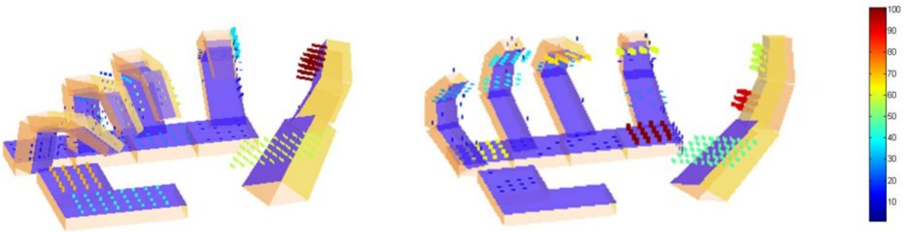

Figure 3. Averaged normalized tactile response overlaid on the grasp configuration. The left image shows the task of hammering with a 3 cm diameter cylindrical handle, the right shows hammering with an 8 cm diameter handle.

We examine the use of our setup in the context of two tasks which require the use of the finger sides. The first task involves hammering with different sized hammers. Figure 3 shows the grasp response captured using our setup. We see that the thumb usage in opposing the fingers has been well captured. The small handle (left image) is gripped by 3 fingers (middle, ring and pinky) opposing the palm. However, the thumb tip in opposition to the side of the index finger also forms an important part of this grasp. For the large handle (right image) the thumb is employed in a different manner, moving across to oppose the frontal finger surfaces and cooperating with them in opposing the palm. Note that the thumb metacarpal is not subject to thumb-twist in the kinematic model thus better capturing the grasping intention of the base of the thumb.

Next we examine the task of writing where the subject is asked to write 3 different letters. In Figure 4 we see that the grasp involves the thumb, index and middle fingers, with the thumb-tip working against the index-tip and side of the middle finger. From the interaction forces we can make out each continuous stroke in forming a letter as well as when the subject lifts up the pen in-between strokes. Further we see that, for the letters demonstrated, while the interaction forces over the task duration are different for each letter, it is always the thumb-tip and middle-side grasping patches that take a dominant role in shaping the letter while the index-tip acts in support.

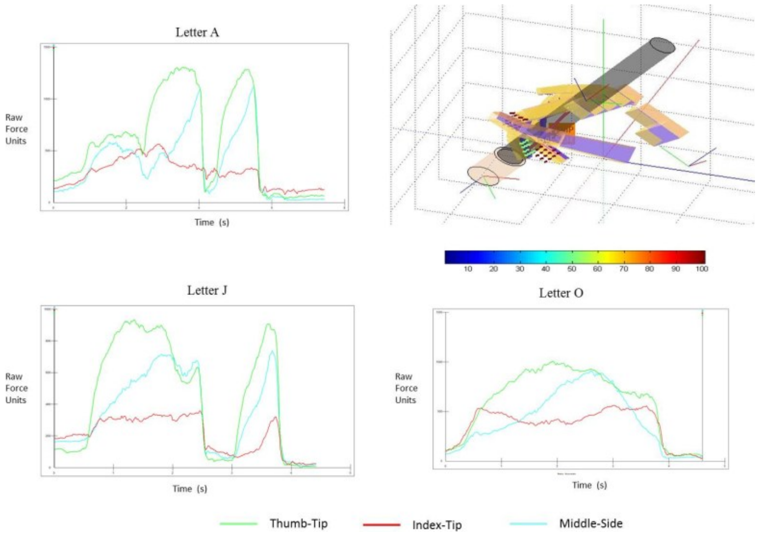

Figure 4. Averaged normalized tactile response overlaid on the grasp configuration for the task of writing

5. DISCUSSION

The state-of-the-art in measuring human grasp response does not account for the sides of the fingers which play an important role in accomplishing several commonly encountered tasks. We address this limitation with a new setup for a "sensorized' data glove and a new calibration procedure to model the nonlinearities in the thumb response. Results show that our method is able to capture both the interaction forces and also the intention of the demonstrator in employing hand parts in opposition especially with regards to the use of the finger sides. This provides a more complete picture for the study of human grasping and manipulation with a view to transferring these skills to autonomous behavior in prosthetic or anthropomorphic robot hands.

6. ACKNOWLEDGMENT

This research was partly funded by a doctoral grant (SFRH/BD/51071/2010) from the Fundação para a Ciência e a Tecnologia and by the Swiss National Science Foundation through the National Centre of Competence in Research (NCCR) in Robotics.

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