Visualization of Grasping Operations based on Hand Kinematics measured through Data Glove *

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ABSTRACT

Although a number of prosthetic hands have been reported, anthropomorphic control is still a challenge. Precise determination of human hand kinematics will certainly enhance the control for prosthetic hands. One of the ways to push the research forward is to measure and visualize the human hand kinematics in real-time during grasping operations. This paper reports the development of a data glove that can measure human hand finger joint kinematics. The measured hand kinematics is visualized for 16 grasp types, adopted from Cutkosky's grasps taxonomy, in SynGrasp MATLAB toolbox. The glove can measure the finger joint angles with an accuracy \pm standard deviation for metacarpophalangeal (MCP) \pm 4°, proximal inter phalangeal (PIP) \pm 2° and distal inter phalangeal (DIP) \pm 2° during flexion/ extension and abduction/ adduction.

Keywords

Hand kinematics, Data glove, Grasp Types

1. INTRODUCTION

Researches on robotic hands in the area of rehabilitation insisted the visualization of hand models based on the finger joint kinematics. This is for emulating the grasping operations with human-like capabilities. In spite of a number

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ÄIR '17, June 28-July 2, 2017, New Delhi, India Copyright 2017 Association for Computing Machinery. ACM ISBN 978-1-4503-5294-9/17/06...\$15.00 https://doi.org/10.1145/3132446.3134905 of researches for last four decades, robotic hands are away from complete comprehension of human hand grasping operations. This necessitates understanding the finger joint kinematics during grasping operations.

Camera-based and glove-based systems have been the two categories for capturing human hand movements [2]. Among these, hand movements recording system using the data glove is of advantage being independent of the ambient light and area of view [14]. A number of commercial versions of data glove have appeared in the market. Visual Programming Language Research Inc., one of the pioneers to commercialize Data Glove used light sources to detect joint angles [22]. It can recognize fine manipulations or complex gestures with low accuracy. Further, the operating speed is insufficient to capture very rapid hand motions [12]. Power Glove from Mattel Intellivision [20] and Super Glove from Nissho Electronics [12] used printed resistive ink to measure joint angles. The use of Power Glove during daily living activities [20] is difficult being heavy in weight as well as the accuracy is low for the kind of sensor in it. The Super Glove can determine only two states of finger flexion using a threshold value on the sensor output. It also requires calibration each time a new user uses it [12]. Virtual Exploration Laboratory, Stanford University developed the Cyber Glove based on piezo-resistive sensors for detection of hand movements [15]. 5DT Data Glove was commercialized by Fifth Dimension Technologies. It is based on the properties of optical-fiber flexor sensors for detecting changes in finger position [3]. These gloves provide information about the extent of finger bending instead of accurate joint angles. Further, the working principle being based on light sources suffers from the ambient light condition [3]. Didji Glove commercialized by Didjiglove Pty Ltd. is based on capacitive sensors [3]. StrinGlove from Teiken Limited uses Inductored for finger movement detection [11], [8]. Both StrinGlove and Didji Glove require calibration each time a new user uses it [11], [3].

A number of hand model visualization tools have been made available as open source. A few of them are OpenGRASP [13], Delmia's IGRIP [7], GraspIt [1], Flow Software Technologies Workspace5 [10], MCS Software's ADAMS [4], Corke's Robotics Toolbox [5], Speck and Klaeren's RoboSiM [19], SynGrasp [16], Roboanalyzer [17]. Most of these tools are used for understanding the concepts of robotics, and visualization of kinematic and dynamic simulations of robotic models. But very few of them have been explored for emu-

lating the human hand kinematics in real-time. Therefore, understanding the hand kinematics and customizing with one of the visualization tools is an opportunity to enhance the research for control of prosthetic hands.

This paper reports the development of a data glove that can measure the finger joint kinematics being independent of the ambient light condition. The measured kinematics for 16 grasp types, adopted from Cutkosky's grasping taxonomy [6], is visualized in SynGrasp MATLAB toolbox. The glove can measure the finger joint angles with an accuracy±standard deviation for metacarpo phalangeal (MCP)±4°, proximal inter phalangeal (PIP) $\pm 2^{\circ}$ and distal inter phalangeal (DIP) ±2° during flexion/ extension and abduction/ adduction of fingers for grasping operations by the user and have been visualized in the SynGrasp toolbox in real-time. Although the work described in the paper rely on the advantages of existing sensor and communication technologies, it can be considered as one of the steps towards the realization of an effective way to measure and visualize the human hand kinematics in real-time during grasping operations to push forward the research on anthropomorphic control for prosthetic hands.

2. METHODOLOGY

Figure 1 shows the methodology for measurement of finger joint angles during grasping operations by the human hand and its visualization in SynGrasp.

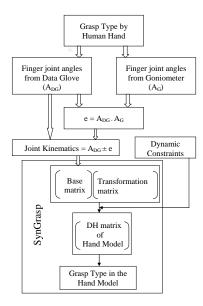


Figure 1: Methodology for measurement of human hand finger joints and its visualization in SynGrasp

The glove customized with angle sensors at the MCP and PIP measures the hand kinematics (A_{DG}) during grasping operations. Finger joints for the corresponding grasp types were also recorded using a stainless steel rotary goniometer (A_G) . Placing the rotary joint of the goniometer on the finger joint to be measured and aligning it along the axis of the finger phalanges during the grasping operations, the goniometer's protractor readings were noted down as the ac-

tual finger joint angles in a database. The difference of the joint angles calibrated from the data glove and goniometer reading is considered as an error (e) and used to minimize the error in measured joint angles. The error minimization was obtained by adding or subtracting the error to the angle measured by the data glove. The DIP joint is determined using the inter joint relationship defined by dynamic constraints [18] as in equation 1.

$$DIP = \frac{2}{3}PIP \tag{1}$$

The measured joint angles (MCP, PIP and DIP) are fed to the human hand model in SynGrasp to modify the transformation matrix according to the grasp type performed by the user. This in turn is used for determining the Denavit Hartenberg parameters of the hand model. Following this, the hand model modifies to the corresponding grasp type.

2.1 Data Glove and Measurement of Finger Kinematics

The data glove system constitutes of a leather glove, 10 accelerometers (ADXL335), a microcontroller (Arduino MEGA 2560), a Frequency Shift Keying (FSK) transceiver module and a visualization unit. The sensors were placed at the MCP and PIP joints on the glove. Figure 2 shows the developed data glove.



Figure 2: Indigenously developed Data Glove

During data acquisition, the subjects wearing the data glove perform the grasp types available in the Cutkosky's grasps taxonomy [6]. The sensors measure the MCP and PIP joint angles of the fingers at different grasp postures. The DIP joint being passive in nature is measured through the dynamic constraints using the MCP and PIP measurement. The used sensor being based on the capacitive sensing mechanism and manufactured through microfabrication technique is expected to outperform the measurement by other data gloves [21]. A total of 20 joint angles have been measured using the angle sensors. Angle sensor changes its output voltage levels for different tilt angles. This property was utilized in our data glove model for calculating the joint angles as the hand performs the grasping operations. For the representation of the finger movements in the angle sensor coordinate system, flexion/ extension angle is made about

the Z-axis of the sensor and abduction/ adduction angle is made about the Y-axis as shown in Figure 3 with the frame at the MCP as reference. The sensor outputs are fed to the microcontroller for calibration into the finger joint angles and transmitted wirelessly to the visualization unit.



Figure 3: Coordinate system for the Angle sensors on one Finger

2.2 Human Hand and Grasping operations

Human hand consists of five digits: four fingers and one thumb. Each finger constitutes of three interlinking segments: proximal, intermediate and distal phalanges. Thumb is made up of only the proximal and distal phalanges. The joints on the finger are named: DIP, PIP and MCP joints [9].

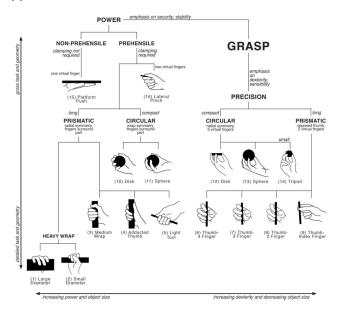


Figure 4: Cutkosky's Grasping Taxonomy (Adopted from [6])

The hand kinematics changes according to the type of grasps. Grasp types are arranged into 16 types in the Cutkosky's grasps taxonomy and is shown in Figure 4 [6]. We have considered these 16 grasp types for the evaluation of the developed data glove.

2.3 Emulation of the Grasping operation in SynGrasp

Figure 5 shows the subject's hand with the data glove performing the 16 grasp types of Figure 4 and their emulation by the hand model in the SynGrasp.

Grasp Type	Human Hand Grasps	In SynGrasp
Large Diameter		
Small Diameter		
Medium Wrap		
Adducted Thumb		
Light Tool		
Thumb-4 Finger		
Thumb-3 Finger	4	
Thumb-2 Finger		

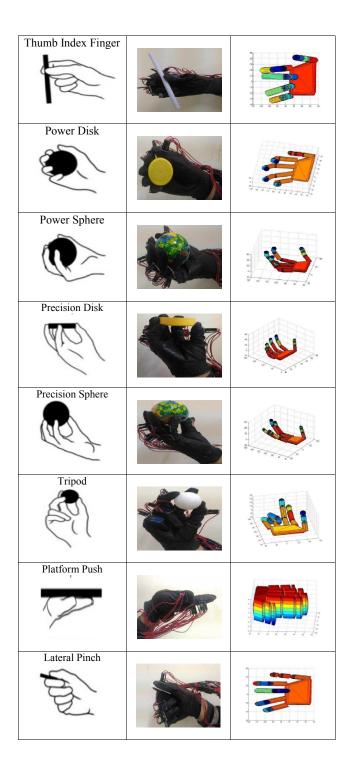
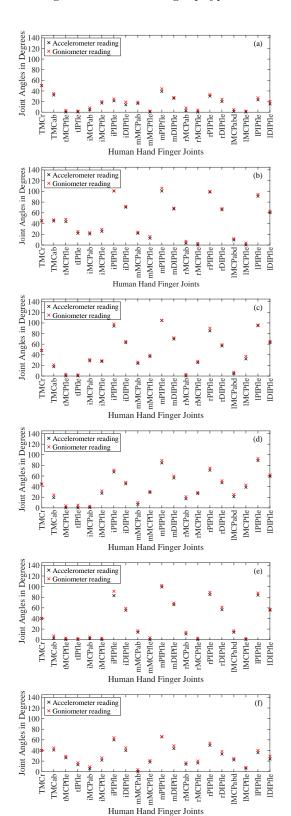


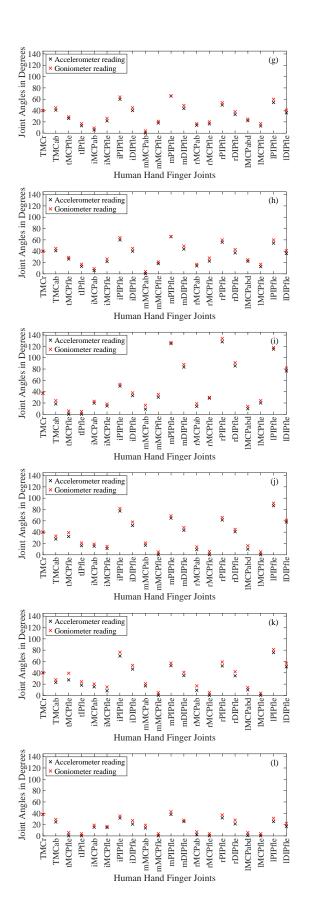
Figure 5: Visualization of Cutkosky's Grasp Types in SynGrasp

SynGrasp can import a wide variety of hand models and can simulate the grasps. The hand kinematics obtained from the data glove were fed as input to the paradigmatic hand model in SynGrasp. SynGrasp follows the methodology shown in Figure 1 using the SGparadigmatic, SGplotHand and SGmoveHand functions defined in MATLAB [16].

3. RESULTS AND DISCUSSIONS

Figure 6(a) through (p) shows the measurement of the finger joint angles using the data glove with error minimization and that of the goniometer for the 16 grasp types under study.





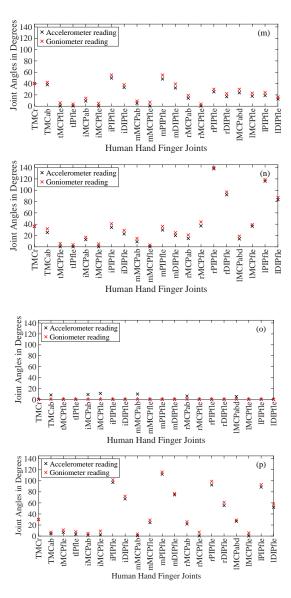


Figure 6: Finger Joint Angle Measurements of the Data Glove and the Goniometer for the 16 Grasp Types: (a) Large Diameter (b) Small Diameter (c) Medium Wrap (d) Adducted Thumb (e) Light Tool (f) Thumb 4 Finger (g) Thumb 3 Finger (h) Thumb 2 Finger (i) Thumb Index Finger (j) Power Disk (k) Power Sphere (l) Precision Disk (m) Precision Sphere (n) Tripod (o) Platform Push (p) Lateral Pinch

In Figure 6, the X-axis denotes the 20 joint angles of the fingers (TMCr = trapeziometacarpal rotation, TMCab = trapeziometacarpal abduction, tMCPfle = thumb MCP flexion, tIPfle = thumb inter phalangeal flexion, iMCPab = index finger MCP abduction, iMCPfle = index finger MCPflexion, iPIPfle = index finger PIP flexion, iDIPfle = index finger DIP flexion, mMCPab = middle finger MCP abduction, mMCPfle = middle finger MCP flexion, rMIPfle = middle finger PIP flexion, mDIPfle = middle finger DIP flexion, rMCPab = ring finger MCP abduction, rMCPfle = ring finger MCP flexion, rPIPfle = ring finger PIP flexion, rDIPfle =

ring finger DIP flexion, lMCPab = little finger MCP abduction, lMCPfle = little finger MCP flexion, lPIPfle = little finger PIP flexion, lDIPfle = little finger DIP flexion). The Y-axis denotes the variation of the joint angles in degrees during grasping operations. Figure 6(a) shows the joint angles for the large diameter grasp type, wherein fingers are not that much flexed for a wider grip. As can be seen, low flexion angles are obtained for this grasp. Figure 6(b) shows the joint angles for small diameter grasp type, wherein the fingers are more flexed compared to the large diameter grasp, for a narrower grip. So high flexion angles are obtained for this grasp compared to the large diameter grasp. This observation is more prominent for the platform push grasp as in Figure 6(o), wherein all the joint angles are approximately zero. The accuracy of the data glove was obtained by finding the standard deviation of the measured joint angles from actual joint angles for the grasp types under study. It has been reported that the glove can measure the finger joint angles with an accuracy±standard deviation for MCP±4°, PIP±2° and DIP±2° during flexion/ extension and abduction/ adduction.

4. CONCLUSIONS

Accurate determination of the finger kinematics for anthropomorphic control for prosthetic hand holds promise. The work reported in this paper pushes the research forward to measure the hand kinematics using an indigenously developed data glove and visualizing the hand kinematics for grasp types in real-time. The developed glove can measure flexion/ extension and abduction/ adduction of the finger joints with an accuracy \pm standard deviation for MCP \pm 4°, PIP \pm 2° and DIP \pm 2° while performing the Cutkosky's 16 grasp types. The measured hand kinematics for the grasp types have been emulated in SynGrasp MATLAB toolbox. These results will extend the laboratory based studies for enhancing control of prosthetic hands.

Acknowledgement

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