ANALYZING GRASPING FOR INFERRING COGNITIVE STATES OF USERS

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ABSTRACT

We study the effect of cognitive states, feelings about tasks, on grasping behavior to estimate user's feelings from their motion. Since people solve the inverse kinematics problem of grasping based on their cognition for the task, when they grasp an object, the way to grasp the object reflects their cognitive states. We are analyzing the way of grasping a cup depending on whether a user is stressed. The physical properties of grasping, volume and entropy of Grasp Jacobian ellipsoids are analyzed. The volume of Grasp Jacobian ellipsoids, which indicates the possible size of object movement, was shrunk after learning the grasp motion. Also the volumes between the relaxed and the stressed cognitive conditions were significantly different. These results show that the user's cognition for tasks reflects the grasp forms and the possible size of object movement.

Index Terms*— *Motion analysis, intelligent sensors, Cognitive science, Kinematics, Jacobian matrice

1. INTRODUCTION

In human-machine interaction, a demand for user-friendly interfaces has been proportionally increased with increasing complexity of machine functionality. For user-friendly interface systems, motion recognition has been widely studied. AcceleGlove, Acceleration sensing glove (ASG) and SCURRY are the gloves which mounted several motion sensors and recognize the user hand gestures and motions[1][2]. Other examples are the game controllers and the mobile phones. These devices recognize the user motions and help the user-intuitive input without wearing any uncomfortable device [3] [4].

These works focus on recognizing physical states of motion such as positions, orientations, speeds and directions. However, inferring user's feelings about tasks also supports user-friendly interfaces. For instance, if a mobile phone detects that the user is stressed while recognizing speech, the speech corpus can be changed.

Our final goal is to infer user's feelings for tasks from a motion sensor embedded object such as mobile phones and small music players. Motion sensor signals from the hand held object are outputs from human grasp motion systems. Grasping an object is the inverse kinematics problem and human solve it by their cognition which reflects user's perception, feelings and knowledge about the world such as objects and tasks [5]. The recent works in neuroscience show that human grasp forms are different under different objects and perception [6][7]. The compatibility of the grasp with the physical requirements of tasks was also studied [8]. We assume that grasping an object also reflects user's feelings and knowledge about tasks, named "cognitive state". If our assumption is correct, user's feelings about tasks can be inferred based on the human grasp model.

The objective of this paper is to investigate the effect of user's feelings and knowledge about tasks on grasping behavior. We studied the simplified problem that grasping a cup filled with water will vary depending on whether the user was stressed. In the condition that the cup has the lid on it, the user feels relaxed to the task while grasping. On the other hand, the user is stressed when the lid of the cup is not attached because the user feels water can spill.

The grasp model used for analyzing grasp behavior is based on a control system. In this model, a user controls object positions and attitudes through Grasp Jacobian. The physical properties of grasping, size and Degree of Freedom (DOF) of potential object movement obtained from Grasp Jacobian, were compared between two cognitive conditions.

In the next section, we define the cognitive states used in this paper then introduce our grasp model and two physical properties of Grasp Jacobian used in analysis. In Section 3, we perform the experiments on a simple task, and discuss our results in Section 4.

2. ANALYSING METHOD

2.1 Cognitive state

While body motions are physical activities, they are influenced by some internal states of a performer. Perception is an example of such internal states [6]. The performer reacts to stimuli. Another example is emotion. The performances of motion are varied under different emotions.

Motions are also influenced by user's cognition about tasks [7]. If the user considers that the task is sensitive, the user will perform accurate motion. On the other hand, the natural motion is expected if the user is relaxed to the task.

We study about such cognitive states, defined as feelings and knowledge about tasks, in this paper. Because of the unknown

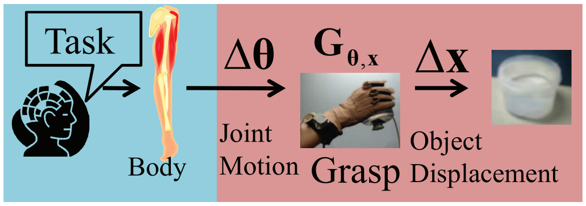


Figure 1: Analyzing model based on human grasp system. The grasp is selected depend on cognitive state.

of cognitive states in our daily life, we focus on only two states, relaxed and stressed, for simplifying the problem.

2.2.Aanalyzing model

For analyzing cognitive states of users, we propose a model that considers motion sensor signals from a hand held object as outputs of human grasp systems.

Because grasping a simple rigid object is a problem of redundant degree of freedom, there is a variety of combinations of finger joint angles for grasping the same object. While robots must solve this inverse kinematics problem based on physical conditions of tasks such as inertia and stiffness, humans can unconsciously determine a suitable grasp form based on their cognitive state.

Figure 1 illustrates our grasp motion model. In our model, a user controls positions and postures of a grasped object through grasping. At the beginning of control, the user determines the appropriate grasp form using their cognitive state and forms it. Then while grasping the object, the user inputs command signals into the body and moves finger joints for controlling the object positions and attitudes.

In this model, grasping is modeled by using Grasp Jacobian $\mathbf{G}_{\boldsymbol{\theta},\mathbf{x}}$, which is determined by finger joint angles $\boldsymbol{\theta}$ and object positions and attitudes $\mathbf{x}$. Grasp Jacobian represents the relationship between small displacements of finger joints, $\boldsymbol{\Delta\theta}$, and an object,$\boldsymbol{\Delta x}$ [9][10].

$$\mathbf{G}_{\boldsymbol{\theta},\mathbf{x}}\boldsymbol{\Delta\theta} = \Delta\mathbf{x} \tag{1}$$

In the point of view of inverse kinematics problem, to determine the appropriate grasp form means finding the optimal grasp Jacobian which satisfies the physical requirements of the task.

2.3. Grasp Jacobian ellipsoid

Grasp Jacobian ellipsoid is a representation of some physical characteristics of grasping $\mathbf{G}_{\boldsymbol{\theta},\mathbf{x}}$ and illustrates the potential area of object movement when norm of finger joint motions $\Delta\boldsymbol{\theta}$ is 1 [10].

$$\Delta\boldsymbol{\theta}^{\mathrm{T}}\Delta\boldsymbol{\theta} = \Delta\mathbf{x}^{\mathrm{T}}\mathbf{G}_{\boldsymbol{\theta},\mathbf{x}}\mathbf{G}_{\boldsymbol{\theta},\mathbf{x}}^{\mathrm{T}}\Delta\mathbf{x}\,, \tag{2}$$

$$\Delta\boldsymbol{\theta}^{\mathrm{T}}\Delta\boldsymbol{\theta} = \Delta\mathbf{x}^{\mathrm{T}}\mathbf{U}^{-1}\boldsymbol{\Lambda}\mathbf{U}\Delta\mathbf{x}\,, \tag{3}$$

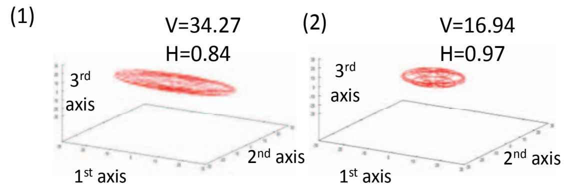


Figure 2: Two examples of Grasp Jacobian ellipsoids. Left ellipsoid is closer to linear so its entropy is lower than right ellipsoid.

$$1 = \Delta\mathbf{x}^{\mathrm{T}}\mathbf{U}^{-1}\boldsymbol{\Lambda}\mathbf{U}\Delta\mathbf{x}\,, \tag{4}$$

$$\mathbf{U}^{-1}\boldsymbol{\Lambda}\mathbf{U} = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}, \tag{5}$$

where $\sqrt{\lambda_1}, \sqrt{\lambda_2}, \sqrt{\lambda_3}$ are axis lengths of Grasp Jacobian ellipsoids.

For investigating physical characteristics of $\mathbf{G}_{\boldsymbol{\theta},\mathbf{x}}$, volume and entropy of Grasp Jacobian ellipsoids are calculated. The volume of the ellipsoid, V, indicates the size of potential object displacement area.

$$\mathrm{V} = \tfrac{4}{3}\pi\sqrt{\lambda_1\lambda_2\lambda_3}\,. \tag{6}$$

The entropy H of Grasp Jacobian ellipsoids depends on the shape of the ellipsoid. If the ellipsoid is exactly sphere, H = 1. As the ellipsoid shape becomes near to thinner, H is decreased to 0. Physically, H indicates the degree of freedom (DOF) of potential object movement.

$$\mathrm{H} = -\sum_{i=1}^{3} \mathrm{p}\left(\sqrt{\lambda_i}\right)\log_3\left(\mathrm{p}\left(\sqrt{\lambda_i}\right)\right). \tag{7}$$

$$\mathrm{p}\left(\sqrt{\lambda_\mathrm{i}}\right) = \frac{\sqrt{\lambda_\mathrm{i}}}{\sum_{j=1}^{3}\sqrt{\lambda_j}} \tag{8}$$

Figure 2 shows two examples of Grasp Jacobian ellipsoids with the volume and entropy values. The left ellipsoid is thinner. Its entropy and DOF of potential object movement are lower than the right ellipsoid.

3. EXPERIMENTAL SETUP

For analyzing the relationship between cognitive states of users and grasping, a simple grasping motion with two cognitive states was investigated. During the experiment, six right-handed experimental subjects were asked to grasp a cup filled with water under two different cognitive conditions. For each condition, the experimental subject grasped and moved the cup for four seconds for 30 trials. Also, to analyze and avoid the effect of learning of the grasp motion, the same experiment was executed for two times.

・Relaxed: with lid **・Stressed: without lid**

Object details

Shape: cylinder
Diameter: 10cm
Height: 8cm
Weight: 500g

Figure 3: Objects under two cognitive conditions.

3.1. Cognitive condition

The experimental subject grasped a cup filled with water under two cognitive conditions. In the first cognitive condition called "relax", the experimental subject grasped and moved the cup with a lid attached. Since the task only requires the natural motion, the experimental subject relaxed to perform it. On the other hand, the lid of the cup was removed in the second condition called "stressed" and the experimental subject was required more sensitive motion. Figure 3 shows the grasped cup for each cognitive condition.

3.2.Learning of grasping

The experimental subjects can learn more appropriate grasp form by sequential motions. The grasp form might be changed during the experiment. To avoid this, the experiment was executed for two times. During the first experiment, the experimental subject might try the variety of grasp forms to find the suitable grasp form. Then the experimental subject used those learnt grasp forms during the second experiment.

4. EXPERIMENTAL RESULT

The Grasp Jacobian ellipsoid and its volume and entropy were calculated for each trial using the data recorded by motion sensors and a data glove. Then the average volume and entropy for each cognitive condition were calculated. Also the variances were calculated to analyze the singularity of Grasp Jacobian ellipsoids through the experiment. Figures 4, 5, 6, and 7 show the average volumes, the standard deviations of volume, the average entropies and the standard deviations of entropy, respectively. These figures show the difference in the average volume and entropy between the subjects. Since the finger configuration like size and length were different for the subjects, Grasp Jacobian used for grasping the cup during the experiments was different for each subject.

4.1. Result on learning

Figures 4 and 6 show that the average volume and entropy were decreased in the 2nd experiment. It means the size and DOF of

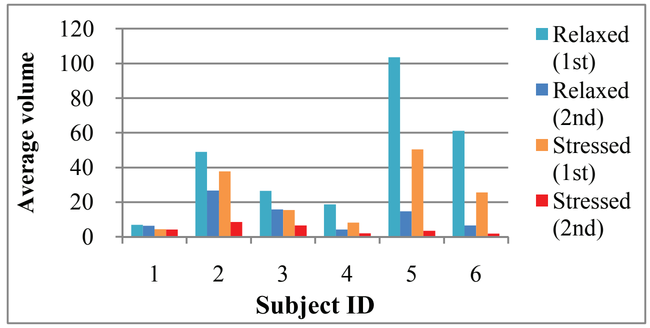


Figure 4: Average volumes of Grasp Jacobi ellipsoids.

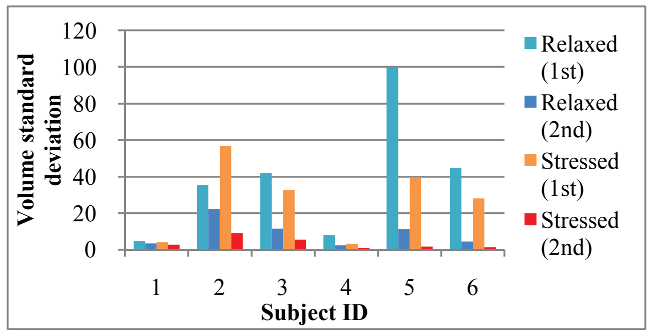


Figure 5: Standard deviations of volume of Grasp Jacobi ellipsoids.

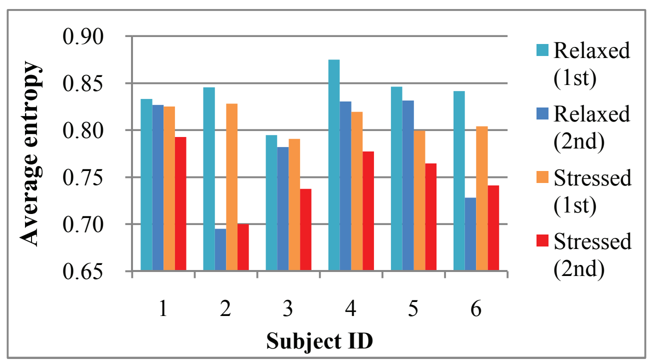


Figure 6: Average entropies of Grasp Jacobi ellipsoids.

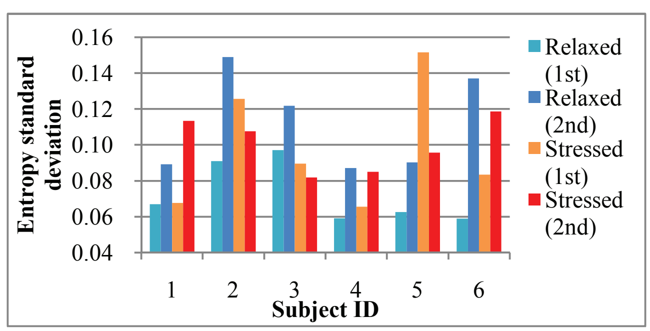


Figure 7: Standard deviations of entropy of Grasp Jacobi ellipsoids.

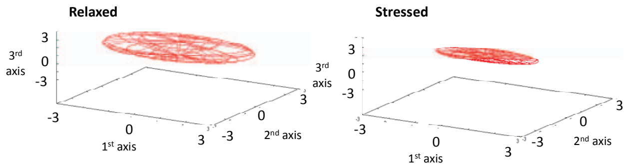
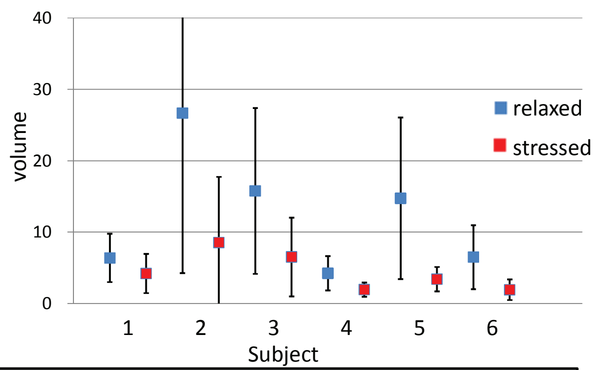


Figure 8: Grasp Jacobian ellipsoids of subject 2 obtained from the 2nd experiment. The volume of ellipsoid under relax condition is larger than stressed condition.



t-test result	0.0083	0.0001	0.0002	0.0000	0.0000	0.0000

Figure 9: Average volumes and standard deviations of volume of ellipsoids in the 2nd experiment. For all subjects, the average volume under relax condition is larger than stressed condition, and these average volumes are significantly different.

movement were decreased after learning. Although the standard deviation of volume were decreased for all subjects, the trend of standard deviation of entropy was increasing. This result indicates that the subjects learned about the size of potential object moving area and was shrunk during the first experiment. In the second experiment, the subjects used the learnt grasp forms.

4.2. Result on cognitive condition

Since the volume of Grasp Jacobian ellipsoid was shrunk through learning, the volume can be considered as the reflection of user's cognitive states. Therefore, we focused on the volume for comparing the cognitive conditions. Figure 8 shows the instances of Grasp Jacobian ellipsoids of subject 2 during the second experiment. Figure 9 represents the average volumes and the standard deviations in the 2nd experiment. In the stressed condition, all subjects have the small volume and the size of potential object movement is small. This result is meaningful because the subjects should carefully control the cup in the stressed condition.

The values, below of the graph in Fig. 9, show the significance probabilities of the test. The null hypothesis of the test is that there is no significant difference in the average volumes between the two cognitive conditions. The null hypothesis can be rejected with the significant level at 0.01 for all subjects. Therefore the volumes of Grasp Jacobian ellipsoids are significantly different between two cognitive states. Consequently the volume of Grasp Jacobian ellipsoid is the effective characteristics for inferring cognitive states from the motion of grasping the cup filled with water.

5. CONCLUSION AND FUTURE WORK

In this paper, we analyzed the characteristics of grasp motion for recognizing use's cognitive states from motion sensor signals. We investigated that the physical properties of grasping a cup filled with water under two cognitive states. The experimental result shows that the size of potential object movement area is shrunk through learning. Furthermore, the volume of Grasp Jacobian ellipsoid indicates the significant difference under different cognitive conditions.

Future works include constructing the model for inferring cognitive states of a user from a motion sensor embedded object.

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