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Design and development of grasping behaviour control strategy for EMG-controlled robotic hand

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Abstract. There are several studies that have examined the control strategy during the interaction of a robotic device while grasping an object. However, there are few research papers focusing on the stabilization of multi-fingered robot hand while picking up an object. In this study, a new set of experiments have been conducted which allow a human participant perform grasping and lifting objects with various total masses to difference targets. Once the human physically grasps the object, the interaction force between human fingers and object is measured by 3D force sensors (OMD-20-SE-40N) which mounted on five fingers. In addition, the object velocity can be estimated using ultrasonic ranging sensor (HC-SR04). To approach design guidelines for grasping an object of a multi-fingered robot hand, the mathematical model of human picking up an object with the influence of variables affecting the finger human fingers force such as masses and displacement targets has been analyzed. By using a mathematical and statistical technique, Box-Behnken design, which is a type of a Response Surface Methodology (RSM) was adopted in order to model and evaluate the functional equation that can be expressed the relationship between influential factors (mass and target) and the human finger force. By applying Analysis of Variance (ANOVA) technique to statistically evaluate the relationship as mentioned, the test results have demonstrated that at least one of the input variables significantly affected the output (human finger force) at the 95% confidence interval. The computed number of R^2 is 0.969, which means that 96.9% of the surface roughness parameter (or predicted finger force) estimation is meaningfully related to the input variable parameters (mass and target). Additionally, it also indicates the third-order polynomial model used to estimate human finger forces is highly reliable. Therefore, the prediction model carried out is assured to be confirmed the appropriateness of the equation and highly reliable.

1. Introduction

Robots are essentially poised to fill a growing number of roles in today’s society; these include applications in automated factories, and medical and other facilities. Robots continue to be successfully employed to improve productivity, quality, accuracy, and reliability. One of the interesting topics is that general-purpose and multifunctional robot hands can be used in a substituted human manual-handling task such as grab, grip, pinch, push and pull. To achieve a conceptual guideline for a robotic human-like control strategy, human behavioral characteristics has to be firstly were investigated. Additionally, such robots need to incorporate high-level safety features in order not to injure people while performing a task.

Over the past few years, much research involving robotic hand development has been significantly carried out for dexterous and skilful grasping applications in medical [1-3]. A robot hand should be, designed as compact and light weight and to be able to move their fingers in a safe and reliable manner before grasping an object with an optimized applied force without damaging the object. [4-6]. A new generation of robot hands is required to apply tactile sensors which can detect forces when touching an object. Many researchers have examined higher forces for finger grasping objects without slipping in object transferring tasks [7-9].

Various technologies, which are used to enable robot hands to be able to estimate grasping force and detect slip have been developed. For example, it can implement vibration-based and object motion based or designed sensors or general force/torque contact sensors. A number of research papers have studied the motion between two-rough surfaces which induces relatively high frequency contact force signals/vibrations during a slip [10-14]. The studies of Johansson and Flanagan [15, 16] show responding of the vibrations induced during slip. High frequency within the range of 5–100 Hz is detected on human-robot object grasping while the relatively low frequency between 0–5 Hz is used for force regulation during stable grasping. One of the interesting topics is related to how to estimate a threshold force during the slip occurred. This can be done using offline training/calibration methods [17, 18] or empirically derived thresholds [15], in which both techniques require a sufficiently rich training dataset and considerable training time.

However, few researchers have studied and developed human finger force characteristics while picking up and lifting (or manipulating) an object in a stable grasp under different masses. These results can be further used as a guideline to design a robot control system for the effective multi-fingered robot hand grasping an object tasks. Consequently, this paper highlights on the development of a behavioral control strategy for a multi-fingered robot hand while grasping and lifting an object; by first understanding the principle dynamics of human behavior, a new set of experiments have been conducted which allow a human participant perform grasping and lifting objects with various total masses to difference targets. In the meantime, finger force, completion time and object position parameters are measure and monitoring. In addition, object velocity and its acceleration can be estimated by using the 1st and 2nd derivative functions respectively. The challenge is further complicated by the dynamic nature of the human-robot environment, which by its nature necessitates very careful design of the control strategy and its implementation in order to protect the human operator from the risk of harm or injury by the robot.

2. Robot hand control schematic

Figure 1 schematically illustrates the overall block diagram of robot hand control. The system involves a set of physical sensors (which include force sensors, and optical absolute encoders), electric linear actuators and a signal conditioning system (such as line driver circuits or instrumentation amplifiers) and a microcontroller. A microcontroller which was used in this research was an Arduino Mega due to the availability, known low-power requirement and ease of use. This microcontroller can generate pulse width signals varied from 600 µs to 1.2 ms over a period of 20 ms in order to control the mechanical robotic hand.

A new AR10 humanoid robot hand with 10 degrees of freedom (DOF) that are servo motors with encoders actuated within the hand's envelope was selected. Anodized aluminium makes up the core of the hand, ensuring a durable and robust, yet lightweight construction whilst plastic linkages and circuit board carriers ensure lightness yet durability. The robotic device provides a complete solution for academia and can be implemented across various applications and interfaces to provide researchers and educators alike with a versatile, low cost platform. The human-like design AR10 device can be setup as a stand-alone platform or attached at the end-effector of a robot arm. The robot fingers have been controlled to suit a wide variety of applications via Windows, Linux, or Arduino. To measure robot finger forces while executing the object manipulation task, Opto-force 3D sensors (OMD-20-SE-40N) were mouthed at the fingertips and the signals were collected in real-time. The sensor measures the magnitude and the direction of forces in x, y and z axes based purely on optical principles with high resolution and high sampling rate up to 1 kHz.

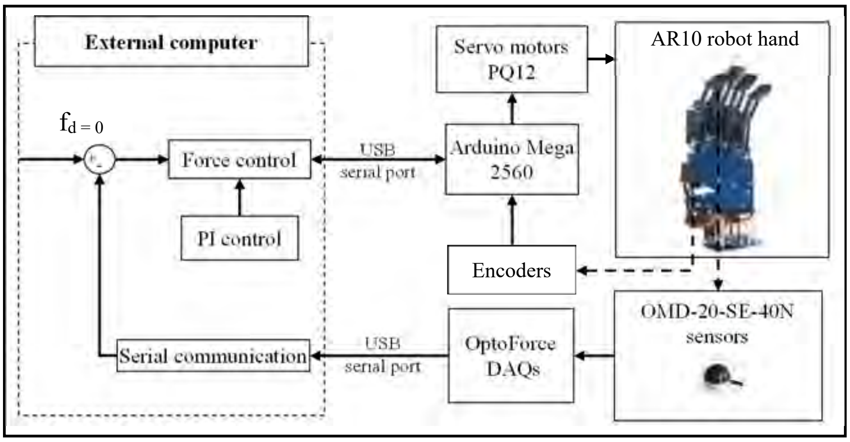


Figure 1. Overall schematic block diagram of robot hand control.

3. Response Surface Methodology (RSM)

As mentioned in Section 1, to understand the principle of human dynamic characteristics when completing human-object manipulation tasks, the tests which allow a human participant perform grasping and lifting objects under various total masses to difference targets have been conducted. These experimental results will be used as a guideline to design and develop a behavioural control strategy for a multi-fingered robot hand.

This section dynamically investigates the relationship between the influential factors (mass and lifting target) affecting the human fingertip forces applied to the object (system output). It is crucial to delivery an appropriate set of experiments, which provide a statistically sufficient amount of complex data while also reducing costs in a timely manner. The Box-Behnken design [19], which is a type of a Response Surface Methodology (RSM) was utilized. The RSM technique is a popular technique to estimate a mathematical model that shows the relationship between output (y) and a group of input variables x_1 and x_2. A third-order response surface is very useful, and is widely used in RSM and it can be presented in Equation (1) [20-22].

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{112} x_1^2 x_2 + \beta_{122} x_1 x_2^2 + \beta_{111} x_1^3 + \beta_{222} x_2^3 \quad (1)$$

where, all unknown coefficient parameters, including β_0, β_1, β_2, β_{12}, β_{11}, β_{22}, β_{112}, β_{122}, β_{111} and β_{222} can be solved using the least square method.

Box and Hunter [19] addressed the term rotatable which means that the predicted variance is the same for every point based on its distance from the center. This method is effectively used for few input variable factors. In this test, the Box-Behnken cube design for two factors (mass and target) is demonstrated in Table 1 in which low, middle and high levels are defined as -1, 0 and 1 respectively. There are 9 different tasks of the Box-Behnken design generated by Matlab software [23].

Table 1. Box-Behnken design

Parameter	Level		
	Low (-1)	Middle (0)	High (1)
Mass (kg)	0.1	0.3	0.5
Height (m)	0.1	0.3	0.5

4. Human Grasping Object

The experimental apparatus is shown in Figure 2, and involves a human participant (randomly selected) to perform the object grasping and manipulating tasks in which the object was attached with a distance sensor (Ultrasonic HC-SR04 sensor). Ten participants were adopted and required to perform a set of random tests in order to become familiar the test rig before completing the substantive experiments. Before the tests were executed, the human was requested to sit down in comfortable position in front of the test rig and his/her fingertips were mounted with the Opto-force 3D sensors. The participant was then instructed to grasp the object with different masses (0.1, 0.3 or 0.5 kg) and move the object vertically to the demanded targets of 0.1, 0.3 or 0.5m using only one hand.

Whilst undertaking the task, three key parameters including object position, completion time and human finger force profiles are measured and collected in real-time for further investigation of the human finger force characteristics. When the object reached the demanded target position, the timer was simultaneously stopped. In the meantime, the LED was activated to indicate that the object was completely reaching to the final position.

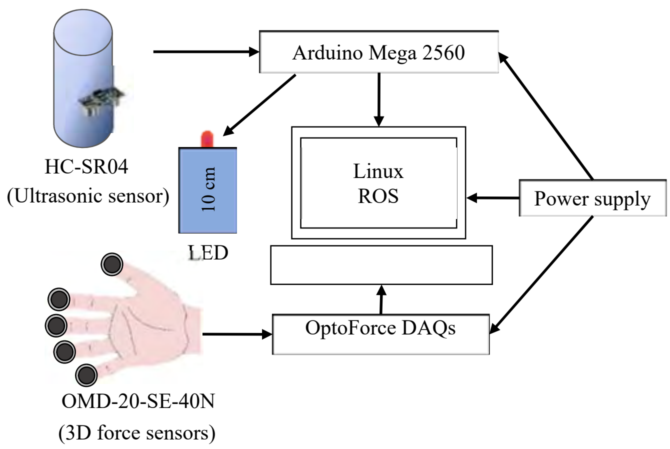
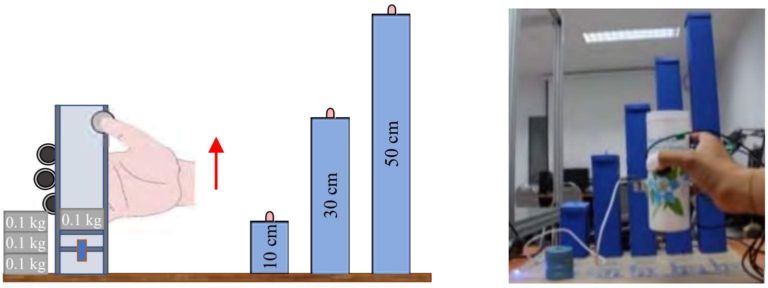


Figure 2. Schematic of force sensor and ultrasonic sensor.

During initially starting each task, the participant has required to perform all assigned tasks to the best of their capacity, and only one hand is allowed to grasp the object and twisting or bending this object is not allowed. The experimental sequence as shown in Figure 3 can be divided into three distinct phases, (i.e. grasping, manipulating and reaching the target), which can be described as the following. In the rasping phase, the human has to naturally grab the object. In the meantime, the micro-controller is activated, and timer trigger is also started. The participant starts moving the object horizontally towards the target point in the object manipulating task. In the last phase, once the LED indicator is turned on and the timer is stopped, that means the object entirely reaches the final position target. After completing an object, the human is then able to release his/her grasp naturally.



(a) (b)

Figure 3. Object manipulating experimental set-up.

5. Estimation of Fingertip Forces during Human Grasping an Object

This section presents the investigation of the relationship of the two influential variables including mass and lifting target affecting the human finger forces applied to the object. During the tests, it can be noted that the finger force profiles are related to how fast the object is moved, i.e. the faster the object is moved to the target, the narrower the force profile is depicted. Therefore, to effectively examine the effects of the relevant parameters, the human finger forces measured were required to be normalized before being analyzed.

The human force profiles while grasping the object were normalized based on an average transfer completion time. The estimation of the third-order polynomial model that demonstrates the relationship between output y (finger force) and the variables x_1 (mass) and x_2 (moving target) was developed using SPSS [24-26]. ANOVA was also used to characterize the output responses for curve fitting and contour plots in which the 95% confidence interval ($\alpha = 0.05$) was adopted.

In this test, the maximum handler forces in each of the Box-Behnken tasks have been highlighted and investigated to deliver the effects of the influential variables proposed. The analysis of variance of the response variables and regression coefficients using SPSS [25] were carried out as shown in Table 2

Table 2. Coefficients of results for the third-order polynomial regression and significant value

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	-2.785	2.733		-1.019	0.324
Mass	62.189	22.174	3.011	2.805	0.013
Height	1.396	22.174	0.068	0.063	0.951
Height*Mass	20.963	48.356	0.454	0.434	0.671
$Mass^2$	-154.331	73.266	-4.569	-2.106	0.052
$Height^2$	-2.579	73.266	-0.076	-0.035	0.972
$Mass*Height^2$	104.167	56.442	1.164	1.846	0.085
$Mass^2*Height$	-164.167	56.442	-1.834	-2.909	0.011
$Mass^3$	203.222	78.704	3.171	2.582	0.021
$Height^3$	-18.667	78.704	-0.291	-0.237	0.816

Once, the parameter coefficients in the third-order equation had been computed and presented in Equation (2), the ANOVA method was subsequently used to assess the system output responses.

$$y = -2.79 + 62.91x_1 + 1.40x_2 + 20.96x_1x_2 - 154.33x_1{}^2 - 2.58x_2{}^2 + \quad 104.17x_1{}^2x_2 - 164.17x_1x_2{}^2 + 203.22x_1{}^3 - 18.67x_2{}^3 \quad (2)$$

Table 3. One-way ANOVA results for the third-order polynomial equation

	Model	Sum of squares	df	Mean square	F	Sig.
1	Regression	206.640	9	22.960	51.480	0.000[b]
	Residual	6.690	15	0.446		
	Total	213.330	24			

Table 4. Result of Model Summary

Model	R	R Square	Adjusted R	Std. Error of the Estimate
1	0.984	0.969	0.950	0.66783

After applying an ANOVA technique to statistically evaluate the equation, it can be concluded that the input variables x_1 (mass) and x_1 (target) significantly affected the dependent output y (finger force) at the 95% confidence interval. Additionally, the computed R^2 was 0.969, which demonstrates that by employing the proposed third-order polynomial equation, 96.9% of the estimation of the human finger force (y) is meaningfully related to the input variables as mentioned as shown in Table 4. Thus, the estimated regression model is highly reliable and acceptable.

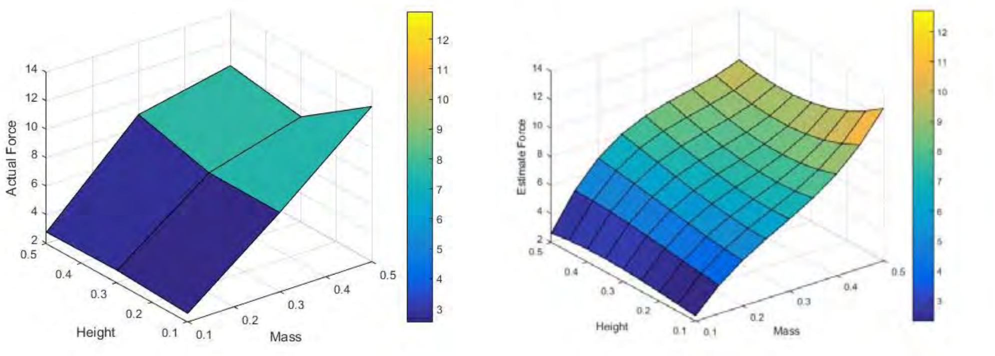
An evaluation of the third-order response surface was performed to ensure its accuracy and reliability. The same group of human participants were selected, in which the humans were required to grasp and lift the objects under the different masses of 0.2 and 0.4 kg and lifting target at 0.2 and 0.4 m. The third-order polynomial equation proposed was employed to estimate the human maximum force (y) values before being were simultaneously compared with the actual results.

Table 5 illustrates a comparison of the predicted dependent variable y (or human finger force) to the actual values. All gray table boxes represent the data designed by Box-Behnken, and on the other hand, the white table boxes show the values used for the evaluation. It can be noted that the maximum, minimum and average absolute errors are 14.0%, 11.54% and 5.22% respectively.

Figure 4 (a) shows a contour of the relation between the mass and the target components and the actual force by using Box-Behnken design 9 different experiments and use to estimate the mathematical model. There are Figure 4 (b) shows the influence between estimated force and a group of input variables (mass and height).

Table 5. Result of estimated force

Total mass (kg)	Height target (m)	Mean of Actual force (N)	Estimated force (N)	Error (%)
0.1	0.1	2.57	2.34	9.00
	0.2	2.61	2.63	0.70
	0.3	2.85	2.85	0.02
	0.4	2.80	2.89	3.35
	0.5	2.78	2.65	4.83
0.2	0.1	4.67	5.17	10.74
	0.2	5.20	5.49	5.59
	0.3	6.33	5.95	5.99
	0.4	5.98	6.44	7.70
	0.5	6.68	6.85	2.50
0.3	0.1	7.55	7.03	6.91
	0.2	7.00	7.05	0.69
	0.3	7.59	7.42	2.26
	0.4	8.77	8.03	8.48
	0.5	8.93	8.76	1.92
0.4	0.1	8.57	9.13	6.51
	0.2	9.34	8.52	8.77
	0.3	8.18	8.47	3.58
	0.4	7.78	8.87	14.00
	0.5	9.68	9.60	0.82
0.5	0.1	12.89	12.69	1.55
	0.2	11.10	11.13	0.25
	0.3	9.42	10.33	9.68
	0.4	11.52	10.19	11.54
	0.5	10.26	10.59	3.22



(a) (b)

Figure 4. (a) Profile of actual force; (b) Profile of output estimation.

6. Conclusion

This research aimed to present the estimated human finger force as a function of time during grasping and lifting an object under the various masses (0.1, 0.3 and 0.5kg) and difference lifting targets (0.1, 0.3 and 0.5m). Response surface methodology (RSM) was employed to explain the input variables x_1 (mass) and x_2 (target) significantly affected the dependent output y (human finger force). By using the ANOVA technique to statistically evaluate the relationship proposed, it can be noted that the computed R^2 was 0.969 which means that 96.9% of the surface parameter y is successfully related to the input variables x_1 *and* x_2 . Therefore, the test results have proved by considering estimate force as mentioned compare with actual force. The results obtained have confirmed by efficacy the calculated mathematical equation from estimated error. It can be noted that the maximum, minimum and average absolute errors are 14.00%, 11.54% and 5.22% respectively. It also indicates the third-order polynomial model used to estimate human finger forces is highly reliable.

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