Shoulder Glenohumeral Elevation Estimation based on Upper Arm Orientation

Sara Hamdan, Erhan Oztop, Jun-ichiro Furukawa, Jun Morimoto, and Barkan Ugurlu

***Abstract*— In this paper, the shoulder glenohumeral displacement during the movement of the upper arm is studied. Four modeling approaches were examined and compared to estimate the humeral head elevation (vertical displacement) and translation (horizontal displacement). A biomechanics-inspired method was used firstly to model the glenohumeral displacement in which a least squares method was implemented for parameter identification. Then, three Gaussian process regression models were used in which the following variable sets were employed: i) shoulder adduction/abduction angle, ii) combination of shoulder adduction/abduction and flexion/extension angles, iii) overall upper arm orientation in the form of quaternions. In order to test the respective performances of these four models, we collected motion capture data and compared the models' representative capabilities. As a result, Gaussian process regression that considered the overall upper arm orientation outperformed the other modeling approaches; however, it should be noted that the other methods also provided accuracy levels that may be sufficient depending on task requirements.**

I. Introduction

Rehabilitation robots have improved the therapeutic quality by enabling longer training sessions and more repetitive and cyclic stimulus [1]. Multiple number of studies have contributed to the robotic therapy devices, for instance, Nef *et al.* developed an upper limb exoskeleton called ARMin III with a biomechanics-inspired shoulder mechanism [2]. Otten *et al.* proposed a self-aligning upper limb exoskeleton called LIMPACT [3]. Ergin and Patoglu designed and developed an upper limb exoskeleton with a special shoulder mechanism to address the self-alignment capability [4]. Ugurlu *et al.* synthesized a controller for upper limb exoskeletons to achieve sensorless force and impedance control [5].

Ensuring the proper alignment between the robot and user joints is one of the key challenges in designing and controlling the exoskeleton [6]. A commonly used assumption in the rehabilitation robotics community is to represent the shoulder glenohumeral (GH) joint as a ball and socket type [7]. This assumption may ignore the vertical and horizontal displacement of the GH joint during the larger motions. Mechanisms with no alignment capability could lead to hyperstaticity and parasitic forces, which may cause severe pain [3], [6], [8].

In order to prevent shoulder joint misalignment, it is desirable to model the glenohumeral elevation. To that end, Nef. *et al.* devised a mathematical tool that considered shoulder adduction/abduction angle as the main parameter [2]. Nikooyan *et al.* developed the Delft Shoulder and Elbow Model (DESM), which comprised inverse-forward dynamics of the shoulder complex [9]. Petuskey *et al.* defended that shoulder flexion/extension angle must be taken into account beside the adduction/abduction angle [10]. Wuelker *et al.* stated that the overall upper arm orientation should be considered [11].

We believe that shoulder misalignment can be prevented by an additional prismatic joint if only glenohumeral elevation is sufficiently modeled. For this purpose, we examined the following four models: i) A biomechanics-inspired model in which shoulder elevation is formulated in terms of shoulder abduction/adduction angle [2]. ii) A Gaussian Process Regression (GPR) model in which shoulder abduction/adduction angle is considered. iii) A GPR model in which both shoulder flexion/extension and abduction/adduction angles are considered. iv) A GPR model in which the whole upper arm orientation is considered using the quaternions representation.

The paper is organized as follows: section II summarizes the models and methods we employed. Section III discusses the results, and section IV concludes the paper.

S. Hamdan, E. Oztop, and B. Ugurlu are with the Faculty of Engineering, Ozyegin University, 34794 Istanbul, Turkey. e-mail: barkan.ugurlu@ozyegin.edu.tr

J. Furukawa, J. Morimoto and B. Ugurlu are with the Dept. of Brain-Robot Interface, Computational Neuroscience Labs., Advanced Telecommunications Research Institute International (ATR), 619-0288 Kyoto, Japan. e-mail: xmorimo@atr.jp

II. Methods

A. Biomechanics-inspired Model

Referring to [2], the position of the humeral head (HH) is expressed as a function of different physical measurements and angles. The model considered the shoulder abduction/adduction movement (the arm elevation angle θ_1) in finding the translation of HH in the x and y directions as shown in Fig. 1.

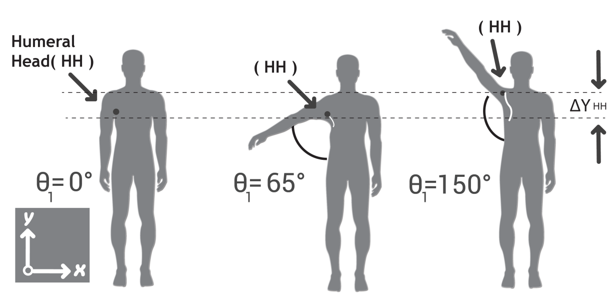

Fig. 1: Humeral Head elevation in the frontal plane

$$
\begin{aligned}
X_{HH} &= -l_c cos(\sum_{n=0}^{5} a_n \theta_1^n) + l_s sin(\sum_{m=0}^{5} a_m \theta_1^m), \\
Y_{HH} &= l_c sin(\sum_{n=0}^{5} b_n \theta_1^n) + l_s cos(\sum_{m=0}^{5} b_m \theta_1^m),
\end{aligned} \tag{1}
$$

In Eq. 1, l_c is the clavicle length and l_s is the distance between the center of the acromioclavicular joint and the glenohumeral joint. Those two parameters together with a_n, a_m, b_n and b_m are the coefficients to be estimated in order to find the translation in the HH in the frontal plane (xy). Nef *et al.* explicitly provided these values based on human biomechanics; however, we used their template model and implemented the least squares method to estimate the parameters l_c, l_s, a_n, a_m, b_n and b_m.

B. Gaussian Process Regression (GPR) Based Models

In supervised learning, it is expected that the points with similar predictor values x_i, naturally have close response (target) values y_i. In Gaussian processes, the covariance (kernel) function expresses this similarity. It simply specifies how much does the knowledge of one point x_i tell us about another point x_j [13].

Although there are many kernel functions that can be used in GPR, probably the most commonly used one is the Squared Exponential Kernel, which we have adopted in the reported study. To assess the predictive capability of the models trained, we used k-fold cross-validation method; which uses models trained on in-fold observations to predict response for out-of-fold observations[1].

The GPR is used in our work to represent the HH translation in terms of different set of parameters. Three models are implemented and compared with the previous model. The first model describes the translation as a function of the shoulder abduction/adduction angle θ_1 as in the previous case, but with the GPR model.

$$(X_{HH}, Y_{HH}) = f(\theta_1) \tag{2}$$

The second model considers the combination of shoulder abduction/adduction (θ_1) and flexion/extension angles (θ_2).

$$(X_{HH}, Y_{HH}) = f(\theta_1, \theta_2) \tag{3}$$

The last model takes the overall upper arm orientation into account in finding the translation values. To represent the orientation, the quaternions were used. The equation is written using three quaternion parameters only (q_x, q_y, q_z); the fourth parameter is not used since it depends on the other three.

$$(X_{HH}, Y_{HH}) = f(q_x, q_y, q_z) \tag{4}$$

The left arm and right arm will have the same equations (Eqs. 1-4), but with different parameters sets.

[1] www.mathworks.com/help/stats/fitrgp.html

C. Data Collection

For proof of the concept, a single able-bodied male volunteer (aged 35) participated. The internal ethics review board of Ozyegin University approved the study. To obtain the required position/orientation variations, an OptiTrack[2] motion capture marker-based system was used. It utilizes retro-reflective markers on pre-designated locations of the body as shown in Figs. 2 and 3. An array of eight cameras were used to track those markers during the movement of the subject. A collection of arm movements via the sole use of the shoulder joint was performed, i.e., elbow and wrist joints remained locked as much as possible. The movements included $3D$ trajectories within the shoulder joint ranges and engaged all shoulder joint axes. The data was recorded using a sampling rate of 250 Hz, and for each experiment, 240 seconds long data was collected. The software platform (Motive) reliably provided marker positions and limb orientations for the subject; see [12].

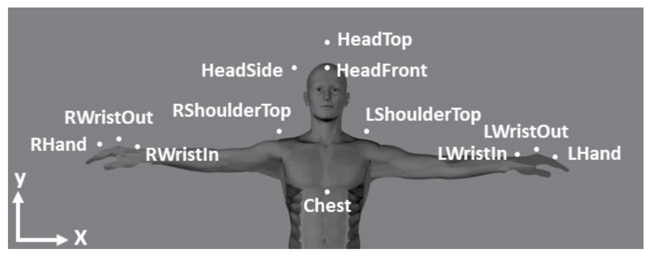

Fig. 2: Front view of the markerset.

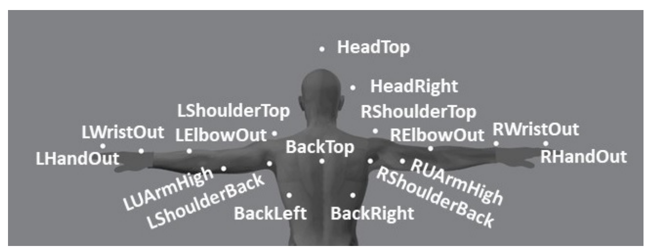

Fig. 3: Back view of the markerset.

III. Results and Discussion

The translation of the human shoulder humeral head was estimated in our work by considering four approaches. In the first one, only the shoulder adduction/abduction angle θ_1 was taken into account to find the vertical and horizontal translational of the HH as in Fig. 1. In doing so, the template model provided by Nef *et al.* was used as a reference [2], an estimation of its parameters was done with the least squares method, based on Eq. 1. The curve fit was done and validated using 7-fold cross-validation method. Fig. 4 shows the fitting result for translation along the x and y axes. We can see from the figure that the model did not fulfill the best fit curve to the measured translation, hence the mean squared error (MSE) gave a value of $2.919e-01$ $[m^2]$ in predicting

[2] http://optitrack.com/

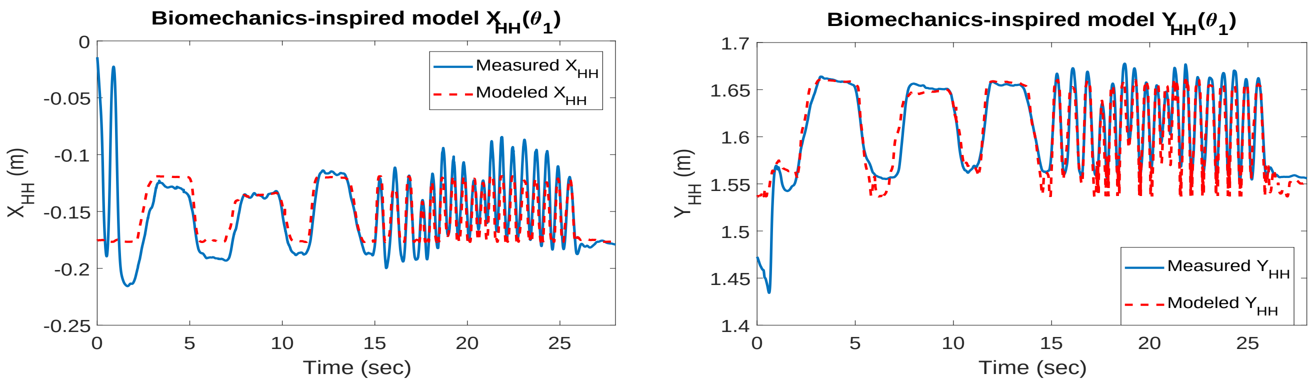

Fig. 4: Humeral Head translation in x & y directions using Biomechanics-inspired model considering θ_1

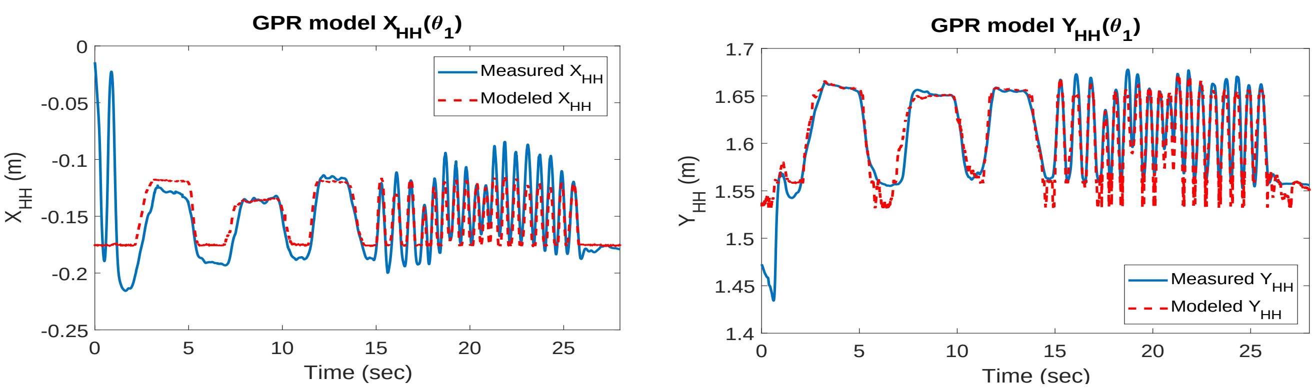

Fig. 5: Humeral Head translation in x & y directions using GPR model considering θ_1

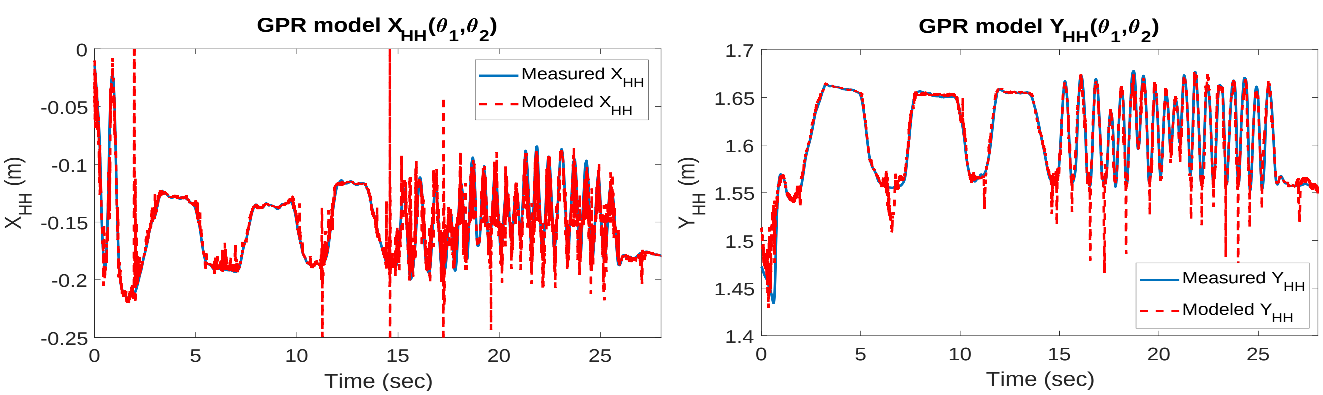

Fig. 6: Humeral Head translation in x & y directions using GPR model considering θ_1, θ_2

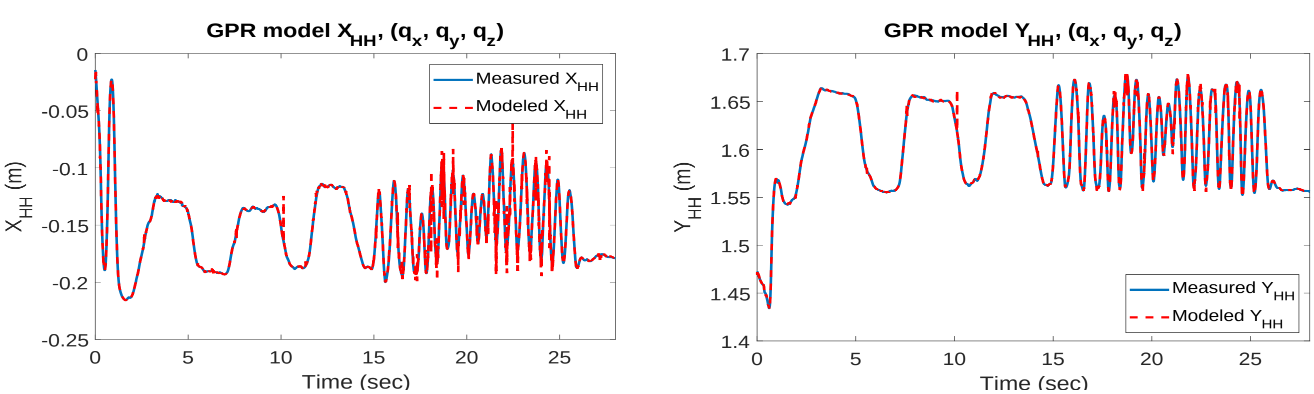

Fig. 7: Humeral Head translation in x & y directions using GPR model considering q_x, q_y, q_z

X_{HH} and $5.279e-02$ $[m^2]$ in predicting Y_{HH} as shown in Table 1; the BioMech. approach (Biomechanics-inspired model approach).

The second approach made use of the GPR model to represent the HH translation, again with the shoulder abduction/adduction elevation (θ_1), as shown in the Fig. 5. The k-fold cross-validation technique was used to validate the result. Comparing to the previous model, using Gaussian process in this approach relatively improved the fitting performance in terms of the prediction error value; referring to Table 1.

As mentioned previously, the shoulder flexion/extension angle can contribute to the humeral head displacement; thus, a combination of shoulder adduction/abduction and flexion/extension angles appears as the third approach. The regression was done again with GPR model and k-fold validation. Fig. 6 displays the fitting result along the x and y axes. In this case, although the error value is similar to the case of using θ_1 alone, there are many undesired peaks which cannot be ignored and should be eliminated using a technique such as median filtering.

Taking the overall upper arm rotation into account is logically the most sensible choice to obtain a comprehensive model that represents the shoulder elevation. Implementing the fourth approach of our study (GPR with quaternions) led to the best prediction result so far. From Fig. 7, we can see that the modeled translation in y-axis is almost matching the measured ones, which is also reflected in the negligible value of the error (in the order of micro); see Table 1. A similar result was obtained for the left shoulder, thus not plotted, but its error values are displayed in Table 2.

Approach	**MSE** X_{HH} $[m^2]$	**MSE** Y_{HH} $[m^2]$
BioMech. (θ_1) [2]	2.919 e-01	5.279 e-02
GPR (θ_1)	5.873 e-04	3.575 e-04
GPR (θ_1, θ_2)	1.909 e-04	1.385 e-04
GPR (q_x, q_y, q_z)	8.111 e-06	2.015 e-06

TABLE 1: Prediction error for the right shoulder

Approach	**MSE** X_{HH} $[m^2]$	**MSE** Y_{HH} $[m^2]$
BioMech. (θ_1) [2]	2.797 e-01	5.092 e-01
GPR (θ_1)	4.246 e-04	2.634 e-04
GPR (θ_1, θ_2)	1.224 e-04	6.037 e-05
GPR (q_x, q_y, q_z)	1.955 e-05	3.808 e-06

TABLE 2: Prediction error for the left shoulder

IV. Conclusion

In this work, we presented a comparative study to represent shoulder glenohumeral elevation. Although the GPR model using quaternions outperformed the other modeling approaches, they all provided a fairly accurate fitting. In terms of the error values, some applications have a big tolerance to error, so a reduction to an error less than millimeter may be good enough. In terms of the smoothness, the first three approaches can give a promising result by the addition of certain filters.

This study provides a proof of concept results and the results were obtained from a single able-bodied subject. More experiments will be conducted to see whether a statistical significance arises between these approaches. In our future work, we will employ the GPR-based approach with a low-cost IMU module that is attached to the user upper arm for controlling our upper limb exoskeleton.

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