Robotic Hand Control with a Remote Sensory Glove

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***Abstract*—This paper presents a technique to control a robotic hand via a remote sensory glove. Five flex sensors are attached to the glove to capture the hand gesture which is then used to remotely control the robotic hand. Due to uncertain behaviour of the signals when sensors are bent, a structured controller consisting of two types of filters and a constraint block has been designed for compensation. The compensator was tested via an experiment with a controlled grab and release hand movement, and the performance is evaluated in terms of the speed when the fingers are bending or flexing, and the mismatch between the actual and expected sensor values when the fingers are stationary. Experimental results show that, with the proposed compensator, the speed is driven closer to the desired value, and the mismatch can be significantly reduced by approximately 45% when the fingers are in the grab position, and 96% when the fingers are totally released.**

***Index Terms*— robotic hand, hand gesture, flex sensor**

I. Introduction

Research on hand gesture recognition has been significantly increased since the past few decades due to advancements in sensor technologies and computing devices. As hand gesture provides a great alternative to verbal communications and benefits those who are incapable to speak in a natural way, studies on sensing and recognition techniques have attracted many researchers especially those in the field of human computer interaction technology [1-3]. This has led to a growing number of innovations in smart assistive devices that are able to capture human gestures with the aid of wearables [4]. Some applications include sign language recognition, goniometric measurements in physical medicine [5], and controlling machines from remote locations with contactless devices [6]. Apart from that, hand gesture can also be used in place of motor or position commands to control a robotic hand [7], which has been extensively utilized in manufacturing industries as well as high risk tasks such as changing nuclear power station, welding and cleaning up radioactive and diverse hazardous wastes. In such cases, the hand gesture approach may be able to provide a relatively more natural movement if one is to precisely control the motion of the robotic hand.

Various techniques have been developed for hand gesture recognition which can be classified into few categories; namely sensor-based method, vision-based method and hybrid approach which combines the sensor- and vision-based methods. The vision-based method usually utilizes cameras or image sensors as primary tools to acquire and extract necessary features for further processing [8].

The main advantage of this method is that it eliminates the need of tactile sensors, hand gloves and the associated building costs. Nevertheless, to obtain a high performance and guarantee its robustness, this method needs multiple cameras at different angles to avoid self-occlusions, which may eventually increase the computational costs [9,10]. Plus, a high specification camera may also be required to minimize the undesirable effects from poor lighting or high-speed movements. The sensor-based technique, on the other hand, relies on instrumented gloves that are fitted with sensing devices such as touch sensors, accelerometer, inertial measurement unit, and flex sensors. The outputs of these sensors are used to measure the degree of bending, orientation, and range of motion of the fingers and/or wrist [5]. Therefore, this method provides a notable advantage over the vision-based approach in the sense that it can directly register the 3D movement of the fingers. Within the sensor-based hand recognition framework, however, numerous approaches have been proposed in the literature which vary in terms of the number and types of sensors used as well as positions of the sensors on the glove. Moreover, as the number of sensors used is increased, the performance can also be enhanced, but it will always come with a higher cost and may pose inconvenience to the users. Hence comparisons between the reported techniques may not be straightforward as there will always be a trade-off between performance, convenience and cost.

In this work, a technique to model and control a robotic hand via a remote sensory glove is presented where a flex sensor is attached to a specific position on each finger of the glove to capture the fingers' angle of movement. Due to uncertain behaviour of the signals when sensors are bent, a structured controller consisting of two types of filters and a constraint block has been

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designed for compensation. The compensator was tested via an experiment with a controlled grab and release hand movement, and the performance is evaluated in terms of the speed when the fingers are bending or flexing, and the mismatch between the actual and expected sensor values when the fingers are stationary. Experimental results show that, with the proposed compensator, the speed is driven closer to the desired value, and the mismatch can be significantly reduced by approximately 45% when the fingers are in the grab position, and 96% when the fingers are totally released.

II. PROBLEM STATEMENT

The flex sensor considered in this work is shown in Fig. 1. It is basically a variable resistor that reacts to bends, i.e. it changes its resistance when bended or flexed. When in default position (i.e. flat), the resistance measures around 25kΩ. The resistance may increase up to 125kΩ as it bends towards 180°. The limitation of this type of sensor is that the bend can only be detected in one direction.

Figure 1. A 2.2" flex sensor.

The sensor can be configured to act as a voltage divider as shown in Fig. 2, where the output, V_{out} is simply the ratio between sensor's own resistance R_1, and the sum of R_1 and an externally connected resistor R_2 This is written as

$$V_{out} = \frac{R_1}{R_1+R_2} V_{in} \tag{1}$$

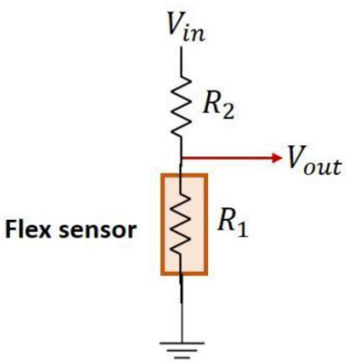


Figure 2. Basic flex sensor circuit.

Theoretically, the resistance increases linearly with bending angle which can be illustrated as in Fig. 3. Hence V_{out} can be easily calculated via (1). When attached to a moving finger, however, the bending angle will not be smoothly increasing or decreasing due to the constraints of the finger's movement. The position of the sensor with respect to the finger may also affect the resistance, leading to unpredictable behaviour.

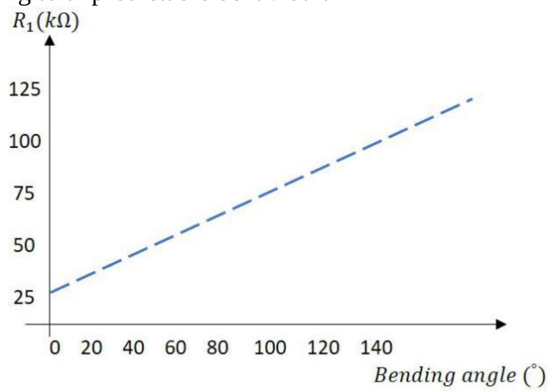


Figure 3. An illustration on the theoretical relationship between R1 and the sensor's bending angle.

The focus of this research is to model a sensory glove consisting of the aforementioned flex sensors, in order to capture precise finger's movement angle and to control a robotic hand from a remote location.

III. METHODOLOGY

In this work, a remote sensory glove is constructed by five 2.2" flex sensors attached to a hand glove as depicted in Fig. 4. The outputs of the sensors are connected to an ATMega microcontroller which uses a 10-bit analog to digital converter. We denote ρ_i as the signals received by the controller where $i = 1,2,3,4$ and 5 correspond to thumb, pointer, middle, ring and pinky fingers respectively. The sensors are positioned in such a way that _is are as close as possible to the angles of bending/flexion of the fingers in degree unit.

Figure 4. The remote sensory glove.

Let θ_i be the angle for each finger with the same index definition as ρ_i. For $i = 2,3,4$ and 5, θ_is are measured from the origins which are placed at the metacarpophalangeal joints, whereas for $i = 1$, the origin is placed at 90° below the thumb's metacarpophalangeal joint. An illustration on the measurement of θ_1 and θ_2 is shown in Fig. 5.

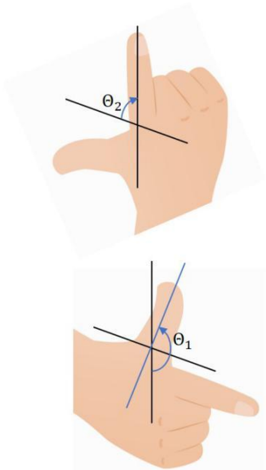


Figure 5. Measurement of θ_2 for the pointer finger movement (top figure); and θ_1 for the thumb movement (bottom figure).

A preliminary experiment with a grab and release movement as shown in Fig. 6 is considered in this work. For performance evaluations, the outputs of the sensors are applied to a servo system as shown in Fig. 7, which will be the input to the robotic hand. The robotic hand considered however may be subject to unknown disturbances, hence its input, Ψ_i, which is the reference command from the servo motor, may not always follow the input ρ_i.

The variations of θ_i were tracked using a camera and an image processing algorithm in MATLAB, while the values of Ψ_i were recorded using the microcontroller. The overall structure of the experimental setup is shown in Fig. 8. Three trials with the same movement were conducted and the corresponding values of θ_i and Ψ_i are recorded. The responses from one of the trails are shown in Fig. 9.

Figure 6. A grab-release-grab movement considered for the experiment.

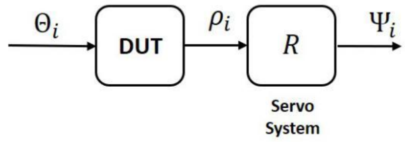


Figure 7. The output of the flex sensors applied on the robotic hand's servo motor system for performance evaluations. The flex sensors are represented by the "DUT" block.

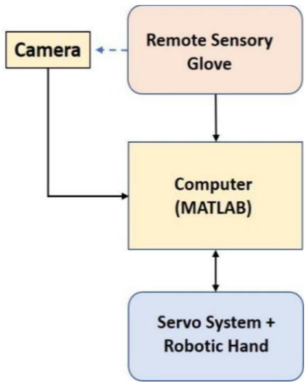
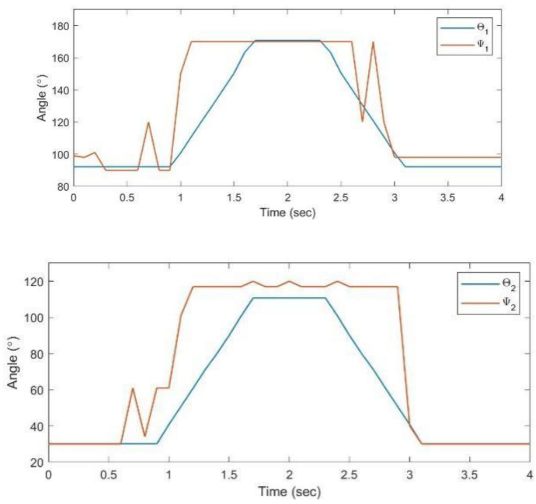


Figure 8. Experimental setup. The camera, robotic hand and the remote sensory glove are connected to a computer for performance evaluation in MATLAB. Black arrows indicate USB connections.

Based on the trials, it can be observed that θ_1 ranges from 90 ° to 171 ° while the rest (i.e. θ_i ($i = 2,3,4,5$)) vary between 30 ° to 110 °. Erratic readings which might be due to noise and disturbances are clearly seen in the beginning and at the end of the movement, where some values go beyond the range of the references. Moreover, small fluctuations can be observed when the fingers are extending while large fluctuations can be observed when the fingers are bending. This will eventually cause an oscillation-like behaviour on the robotic hand. Another undesired behaviour is seen when the slope is relatively higher than that of θ_i, which indicates that the corresponding fingers of the robotic hand will extend or bend much faster than expected.

In order to minimize the mismatch between θ_i and Ψ_i, a compensator consisting of a median filter, M, a constraint block, N, and a first order linear filter, L, in cascade with each other is proposed as shown in Fig. 10.



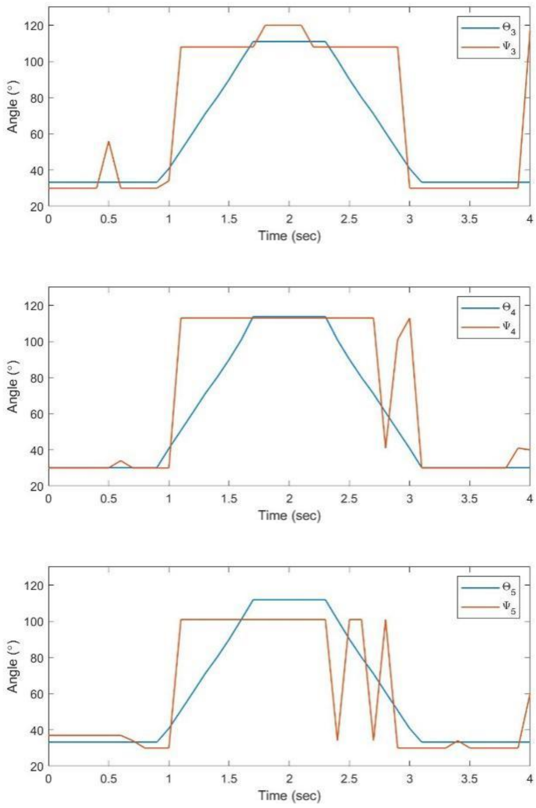


Figure 9. Variations of θ_i (in degree) and the corresponding Ψ_i when there is no compensator for one of the trials.

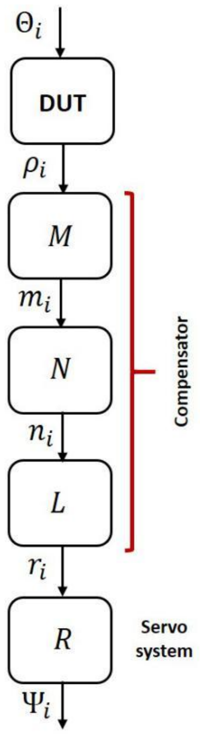


Figure 10. The output of the compensator applied on the servo system for performance evaluations.

The raw sensor data will be first fed into the median filter, *M*, which can be processed as illustrated in Fig. 11:

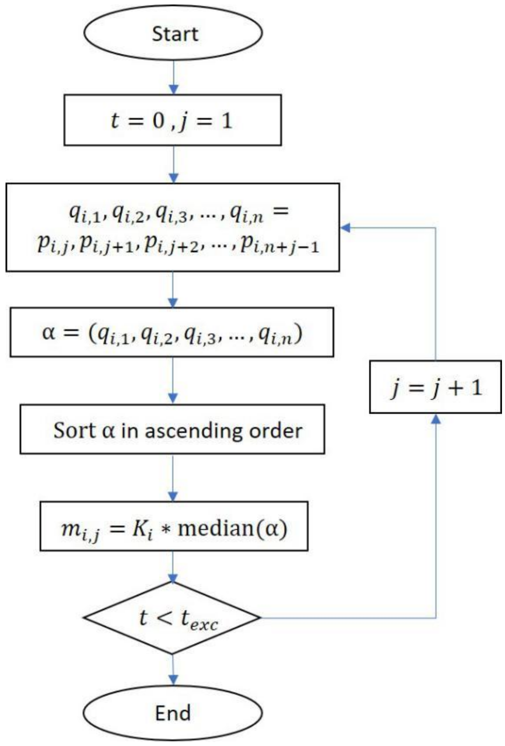


Figure 11. Overview of the algorithm in *M*.

where n is order of the filter, t_{exc} is the execution time, and K_i is a linear gain. The constraint block is included at the output of M to pose lower and upper bounds on the sensor data as follows:

$$\mathrm{N}_i(m_i) = \begin{cases} m_{li} & if \quad m_i < m_{li} \\ m_i & if \quad m_{li} \le m_i \le m_{ui} \\ m_{ui} & if \quad m_i > m_{ui} \end{cases} \qquad (2)$$

From several experiments, the values of K_i, m_{li} and m_{ui} are predetermined as follows:

$$(K_1, K_2, K_3, K_4, K_5,) = (1.05, 1.00, 1.01, 1.01, 1.00) \qquad (3)$$

$$(m_{l1}, m_{l2}, m_{l3}, m_{l4}, m_{l5},) = (92.1, 30.13, 33.25, 30.12, 33.25) \qquad (4)$$

$$(m_{u1}, m_{u2}, m_{u3}, m_{u4}, m_{u5},) = (170.8, 110.8, 111, 113.8, 111.9) \qquad (5)$$

In order to reduce the rise time of the sensor output when the fingers bend or extend, the output of the constraint block is fed into the linear filter $G = diag(G_1, G_2, G_3, G_4, G_5)$ where

$$G_i = \frac{8}{s+8}, \quad for \ \ i = 1,2,3,4,5 \qquad (6)$$

For performance evaluations, the remote sensory glove with the compensator is also tested on the robotic hand as illustrated in Fig.8. The results are presented in the next section.

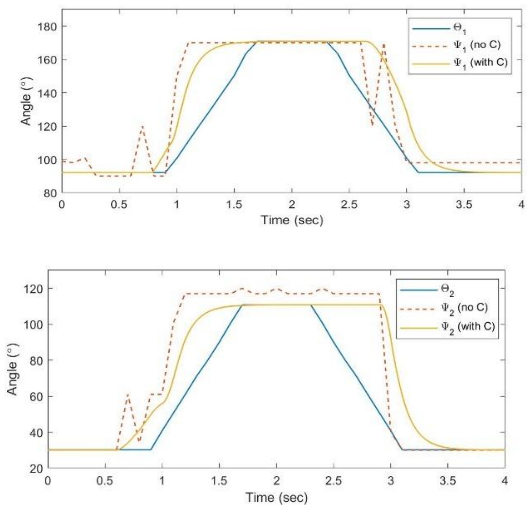
IV. Experimental Results and Performance Evaluations

With a controlled grab and release movement as shown in Fig. 6, the experiment when the compensator is included is conducted for three times. The variations of θ_i and Ψ_i, from one of the trials when the compensator is and is not included are shown in Fig 12. From the figure, it can be observed that the mismatches between θ_i and Ψ_i are minimized with the compensator. The error reduction can be clearly seen when the fingers are stationary, which are represented by the horizontal blue line, and when the fingers are bending or extending, which are represented by the blue slopes.

As a measure of performance, we evaluate the speed in terms of the rise time, t_r, when the fingers bend or extend, and the mismatch between θ_i and Ψ_i , denoted by e_s, when the fingers are stationary. The value of t_r is defined as the time for the signal to rise from 10% to 90% of its steady-state value, while the value of e_s is simply the error between the true and expected signals, which can be mathematically described by:

$$e_{sj} = \int_{t_s}^{t_f} |e(t)|dt, \;\; e_i(t) = \theta_i - \Psi_i \tag{7}$$

where t_s and t_f are the initial and final time recorded when there is no finger movement, and *j=1,2,* and *3*, which correspond the first, second and third stationary time frame. Table I shows the average rise time for each finger for both cases, i.e. when the compensator included, denoted by "With C", and when there is no compensator, represented by "No C". The expected rise time is approximately 0.76s, but when there is no compensator used, the rise time is approximately 0.18s, which indicates that the fingers will bend or extend much faster than expected. On the other hand, with the use of compensator, the rise time can be increased up to approximately 0.55s, which is closer than the expected value.



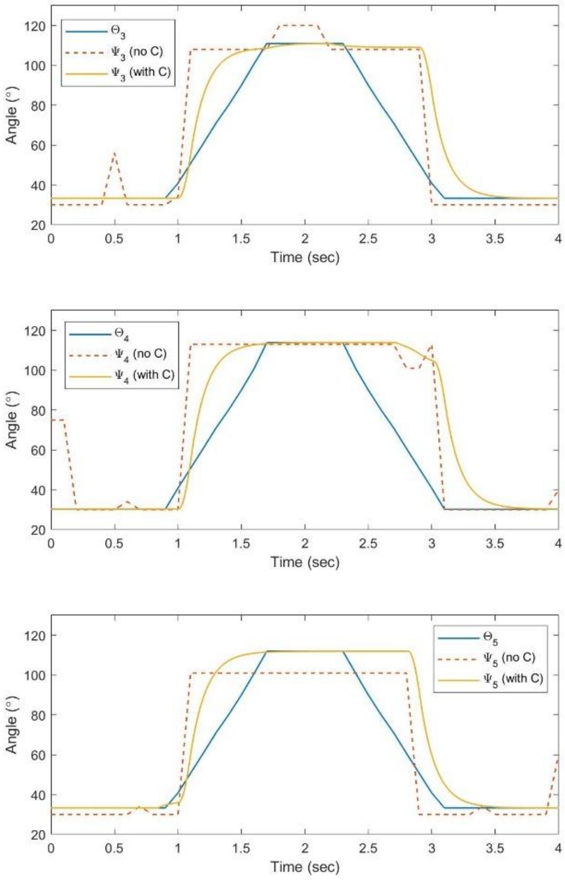


Figure 12. Variations of θ_i (in degree) and the corresponding Ψ_i with compensator (with C) and without compensator (no C) from one of the trials.

TABLE I. Average Rise Time for Each Finger

i	$\boldsymbol{t_r}$(s)		
	No C	With C	Expected
1	0.20	0.55	0.77
2	0.18	0.57	0.75
3	0.17	0.56	0.77
4	0.19	0.57	0.76
5	0.16	0.53	0.76
Average	0.18	**0.55**	0.76

With regard to the mismatch between θ_i and Ψ_i, we divide the stationary region into three parts; (1) for j=1, $t_s = 0s$ and $t_f = 0.91s$, (2) for j=2, $t_s = 1.72s$ and $t_f = 2.31s$, and (3) for j=3, $t_s = 3.1s$ and $t_f = 4s$. The corresponding errors are recorded in Table II.

TABLE II. AVERAGE ERROR FOR EACH FINGER

i	e_{s1} (°s)		e_{s2} (°s)		e_{s3} (°s)	
	No C	With C	No C	With C	No C	With C
1	51.9	7.29	5.20	0.70	52.7	19.5
2	52.4	25.8	42.5	0.46	1.13	35.9
3	43.2	0.04	37.7	3.77	29.3	28.9
4	69.4	1.58	4.90	0.76	6.37	67.9
5	25.6	0.57	66.4	0.66	35.6	14.3
Average	48.5	**7.06**	31.34	**1.27**	**25.0**	33.3

For j=1, which corresponds to the grab position before the fingers start to release, the error is significantly reduced from 48.8°s to 7.06°s when the compensator is included. A quite similar improvement is observed when j=2 where the error is reduced from 31.34°s to 1.27°s. However, for j=3, which corresponds to the instance when the fingers are in the grab position again, the error is slightly increased by 8.3°s.

With the compensator, the average error reduction when the fingers are stationary and in the grab position is approximately 45%, whereas that when the fingers are stationary and vertically stretched is around 96%.

V. DISCUSSIONS AND CONCLUSIONS

In this work, a technique to model and control a robotic hand via a remote sensory glove is presented where a flex sensor is attached to each finger of the glove to capture the angle of movement. Due to uncertain behaviour of the signals when sensors are bent, a structured controller consisting of two types of filters and a constraint block has been selected for compensation. The compensator was tested via an experiment with a controlled grab and release hand movement, and the performance is evaluated in terms of the speed when the fingers are bending or flexing, and the mismatch between the actual and expected sensor values when the fingers are stationary. Experimental results show that, with the proposed compensator, the speed is driven closer to the desired value, and the mismatch can be significantly reduced by approximately 45% when the fingers are in the grab position, and 96% when the fingers are totally released. Nevertheless, the error is slightly increased when the fingers are in the grab position for the second time.

For future work, the structure of the compensator can be improved to further minimize the error. Several trials for other hand gestures may also be included in the experiments, and an image processing may be used to localize the robotic hand to ensure robustness of the compensator.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

S. A. A. S. Mubarak Ali and N. S. Ahmad conducted the research; S. A. A. S. Mubarak Ali conducted the experiments; S. A. A. S. Mubarak Ali analyzed the data; S. A. A. S. Mubarak Ali wrote the paper; N. S. Ahmad validated the results; all authors had approved the final version.

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