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Development of a Wearable Human-Machine Interface to Track Forearm Rotation via an Optical Sensor

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***Abstract*— The goal of this research was to develop an intuitive wearable human-machine interface (HMI), utilizing an optical sensor. The proposed system quantifies wrist pronation and supination using an optical displacement sensor. Compared with existing systems, this HMI ensures intuitiveness by relying on direct measurement of forearm position, minimizes involved sensors, and is expected to be long-lasting. To test for feasibility, the developed HMI was implemented to control a prosthetic wrist based on forearm rotation of able-bodied subjects. Performance of optical sensor system (OSS) prosthesis control was compared to electromyography (EMG) based direct control, for six able-bodied individuals, using a clothespin relocation task. Results showed that the performance of OSS control was comparable to direct control, therefore validating the feasibility of the OSS HMI.**

I. Introduction

A human-machine interface (HMI) provides a means of communication between humans and devices [1], [2]. Applications of HMIs range from manufacturing, unmanned vehicles, assistive robotic devices, training, and virtual reality. With the development of advanced robotic systems, such as robotic hand prostheses and industrial manipulators, human operators are often required to handle challenging tasks using robotic systems with multiple degrees of freedom through HMIs. To reduce the mental load involved in controlling these robotic devices, intuitiveness becomes a key issue for success of HMI design.

As shown in [3], an intuitive HMI permits users to interact effectively, non-consciously using previous knowledge that is classified as innate, sensorimotor, culture, or expertise, based on when and how the knowledge is learned. Generally speaking, the earlier knowledge is learned, the easier the knowledge can be adopted non-consciously. Innate knowledge is limited to reflexes or instinctive behavior, which are not very useful in conducting specific tasks. Therefore, an HMI that optimizes for sensorimotor knowledge, such as natural motions of joints, is expected to deliver the best intuitiveness. One successful example of intuitive HMIs is pattern recognition (PR) control for upper limb protheses, which correlates the prostheses' action with natural hand movements. PR control has been shown to impart less cognitive workload on the user and allow for faster task completion time, compared to direct control, which relies on expertise gained through training after amputation [4]–[6].

As with every wearable system, a wearable HMI needs to minimize its obstructiveness [7], which is evaluated by how it impedes wearers from conducting other tasks. Because hands are often needed to conduct versatile functions in unexpected environments, a wearable HMI to mimic hand motions needs to maintain a low profile and minimize the number of involved sensors to reduce its obstructiveness. Other requirements include reliability for long-term usage and easy don/doff.

Forearm rotation, or pronation and supination of the wrist, is regarded as a critical function for hand manipulation [8]–[10] and is involved in many daily activities, such as opening a door or pouring liquid into a cup. Similar functions are provided in various robotic manipulators, such as 10S17 Electric Wrist Rotator (Ottobock, Germany) and RTE 400 (IGM, Austria). However, HMIs that permit intuitive control of these robotic manipulators, based on forearm rotation of human operators, still need further development.

Existing wearable HMIs that track wrist pronation/ supination can be classified into two groups based on whether the wrist kinematics is measured or not. The most commonly adopted wearable sensor to measure wrist kinematics is an inertial measurement unit (IMU) [11], [12]. Although IMU sensors are easy to mount and calibrate, at least two IMUs are necessary to monitor the continuous wrist movement and the two-sensor setup increases the obstructiveness. Another wearable device to measure wrist kinematics is a torsiometer, such as the Vital sign sensor Z110 (Biometrics Ltd, United Kingdom), which measures the torsional motion of the forearm through the use of a strain gauge [13], [14]. This sensor has a limitation for long-term use because of its finite lifecycle [14].

User intention of forearm rotation can also be identified based on activity of forearm muscles. Surface electromyography (EMG) [15] and ultrasound images measured by wearable ultrasound probes [16] are standard approaches to monitor these muscle activities. However, because the muscles, which drive the wrist pronation/ supination, are either deep inside the forearm or also drive other upper limb motions, it is impractical to link any surface EMG measurements directly to the forearm movements. Advanced data analysis based on pattern recognition or neuromuscular models is needed to maintain intuitiveness of the HMI [5], [17], [18]. Signal fluctuations from electrode-skin impedance, electrode shift, and muscle fatigue [19]–[21] often hinder the reliability of the EMG based HMIs. Although

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ultrasound imaging can be used to monitor the activities of deep muscles, the use of gel impedes long-term usability [22].

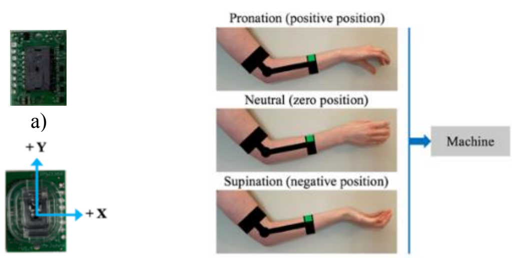
This research proposes an innovative approach to measure forearm rotation using an optical sensor system (OSS) that has the potential to result in an intuitive wearable HMI. An optical sensor was chosen because of its low profile and its capability to track kinematics accurately through noncontact measurements, which ensures its longevity. Additionally, previous work for non-HMI systems have utilized an optical sensor to monitor relative displacement [23]–[26]. By mounting one optical sensor on the forearm using a small orthosis, the proposed HMI could track the wrist motion without impeding wearers' capability to conduct other tasks.

The objective for this research was to develop an HMI that implements an optical sensor to quantify wrist pronation/ supination. The optical sensor system was developed and a bench test was performed to evaluate its accuracy. To test feasibility of the OSS as an HMI, we applied the HMI to control a prosthetic wrist rotator, for able-bodied individuals. The measured wrist rotation was quantified and utilized as the control input to the MC Wrist Rotator of the Utah Arm (Motion Control, Inc., Salt Lake City, UT) prosthesis. The performance of OSS based control was compared to an EMG based direct control using a clothespin relocation task.

II. Methods

A. Optical Sensor System Design

The OSS consisted of an optical sensor, printed circuit board, lens, and an Arduino Leonardo microcontroller. The optical sensor used was the PMW3360 Motion Sensor (JACK Enterprises, Cookesville, TN), which implements PixArt's PMW3360DM-T2QU: Optical Gaming Navigation Chip (PixArt, Taiwan) intended for gaming computer mice, Figure 1 a) and b). The sensor was chosen for its high resolution and accuracy. It uses a navigation chip and an infrared LED to calculate motion along the x and y axes. The chip has an adjustable resolution of up to 12,000 counts per inch (CPI) with a step size of 100 CPI, a resolution error of 1%, a maximum distance of 3 mm from the lens to the moving surface, and utilizes four wire serial peripheral interface (SPI) communication.



b) c)

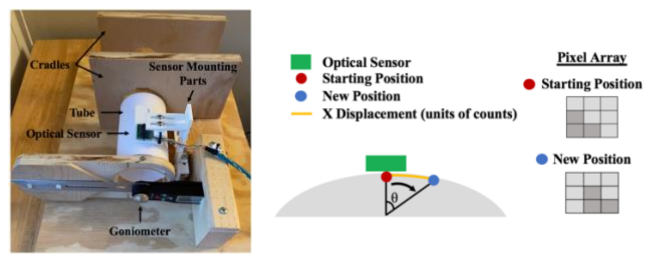
Figure 1: Optical Sensor and OSS HMI Conceptual Diagram. *a) Sensor top b) Sensor bottom with labeled axes c) The black part is the orthosis and the green rectangle is the optical sensor.*

Only one optical sensor was required and the housing, designed in accordance with the sensor's datasheet, was approximately 34 mm x 27 mm x 12 mm, which minimized obstructiveness. The optical sensor should be mounted to a small orthosis, which is secured above the elbow joint to allow the relative motion of the forearm to be measured. The neutral forearm position of 90° between supination and pronation is defined as zero position. Wrist pronation yields a positive position, and supination yields a negative position, Figure 1 c).

B. Bench Test

The use of an optical sensor for measuring rotation was validated with a bench test, Figure 2 a). This consisted of rotating a tube beneath the optical sensor, at two different speeds, and comparing the calculated degrees to a ground truth value from a digital goniometer. The digital goniometer (Husky, Atlanta, GA) has a range of 0 to 360°, accuracy of +/- 0.30°, and an incremental resolution of 0.05°. The tube was positioned inside two wooden cradles that restricted vertical and horizontal motion.

Both measurement systems were zeroed at the beginning of each trial. The tube was rotated counterclockwise by hand from a 0° reading on the goniometer to the desired angle. The angles tested were 5 to 50° in increments of 5°. Three trials of each angle were tested for two speeds: 2.5°/s and 5°/s. The degrees rotated were calculated from the x displacement value, in units of counts, Figure 2 b). The counts were accumulated over time and divided by the resolution to obtain the arc length. To determine the angle in degrees, the arc length was divided by the radius of the tube.



a) b)

Figure 2: Bench Test Setup and Rotation Measurement Diagram. *b) How the sensor calculates degrees rotated, θ, showing a simplified pixel array. The sensor compares consecutive pixel arrays to calculate displacement.*

C. Prosthetic Wrist Rotation Control Development via OSS

The OSS was tested for the wrist pronation/supination control of an upper limb prosthesis, employing open loop proportional velocity control, Figure 3. Intuitive control was implemented, where the direction of the prosthetic wrist was dependent on the direction of forearm rotation and the speed was proportional to the forearm position.

The arc length formula used for the bench test could not be implemented since the forearm is not cylindrical; instead, the raw sensor value, in units of counts, was utilized. The Arduino retrieved the x displacement value continuously from the optical sensor, which was then polled by MATLAB using serial communication. An adjustable deadband was applied to prevent prosthetic wrist rotation for very small movements of the forearm, to eliminate unintended motion. The change in position value was accumulated to estimate the position of the forearm. When the position was greater than an upper threshold, the wrist pronated; when it was less than a lower threshold, the wrist supinated; and when it was between the two thresholds, the wrist was stationary. Subsequently, it was determined if recalibration should occur. Next, the position value was multiplied by a gain to create a voltage. This was added to a base voltage, the minimum voltage for motor movement, and applied directly to the wrist motor. The OSS control utilized the human in the loop method; through visual and proprioceptive feedback, the user was able to close the loop and control the prosthesis as desired.

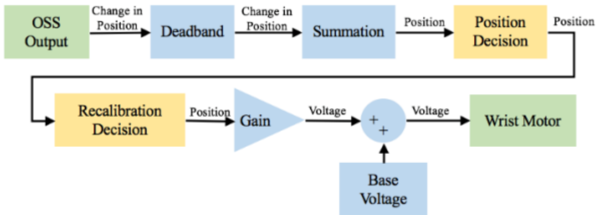


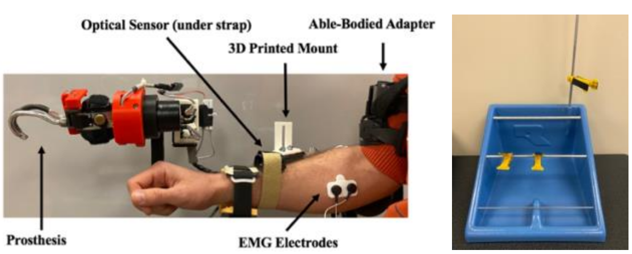
Figure 3: Wrist Rotation Control Block Diagram. *Green blocks show the inputs and outputs to the system. Blue blocks show operations or constant values. Yellow blocks show decisions.*

A recalibration decision was implemented to eliminate the effects of measurement drift. During pronation or supination, when a quick motion to the neutral position was made, the sensor was zeroed, by setting the position to 0, and the wrist control paused for a set amount of time. This pause allowed the participant time to rotate their arm to the neutral position. This method was chosen because it was a simple way to allow the user to recalibrate the sensor and bypass the effects of measurement drift.

D. Experimental Design of Upper Limb Prosthesis HMI

To evaluate the performance of the OSS control it was compared to direct control (DC) [5], via a clothespin relocation task (CRT), for six able-bodied individuals ranging in age from 22 to 45 years. A 2 degree of freedom (DOF) prosthesis with wrist pronation/supination and hand open/close capabilities was utilized. EMG signals controlled both DOF for DC and hand open/close for OSS control. A housing for the OSS was designed to mount it to an able-bodied prosthesis adapter, Figure 4 a). The design consisted of 3D printed parts that allowed adjustments in the vertical, horizontal, and proximal/distal directions. An elastic strap was implemented to maintain contact between the skin and sensor housing.

The CRT, Figure 4 b), was chosen to evaluate the performance because it has previously been used in studies to compare and evaluate upper limb control techniques [4]–[6], [17]. The task completed using the CRT was moving three clothespins between the middle horizontal and vertical bars, as fast as possible for two minutes. It was chosen because it required the prosthetic wrist to move between 0 and 90°.



a) b)

Figure 4: Experiment Devices. *a) Able-bodied prosthesis adapter setup b) Clothespin Relocation Task.*

This study was conducted with IRB approval and informed consent was obtained from all participants. The order of control methods was randomized. After the control parameters were tuned, the participants were given five minutes to practice before performing five trials of moving clothespins.

III. Results and Discussion

A. Bench Test

There was a linear relationship between the ground truth values and OSS values, with correlation coefficients for both speeds greater than 0.99, Figure 5. The maximum deviation of the OSS angle calculation, compared to the ground truth, was approximately 2.5° for angles less than or equal to 55°. This accuracy was acceptable for the application of prosthetic wrist pronation/supination control. The variation in the linear relationship was expected, considering that the tube was rotated by hand. As the rotation increased the difference between the two measurement systems also increased, which is due to an accumulation of integration error.

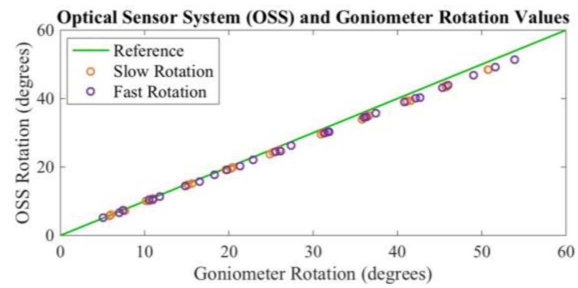


Figure 5: Bench Test Results. *Goniometer rotation values plotted versus the OSS values, for slow and fast speeds. The reference line shows the ideal relationship.*

B. Upper Limb Prosthesis HMI

The number of clothespins moved was used as the metric for evaluation. The average number of clothespins moved across all participants for OSS control and DC was 8.93 and 9.03, respectively. A paired t-test, with a 5% significance level showed that the difference between these averages was not statistically significant. The average number of clothespins was greater for DC for four out of the six participants. The maximum number of clothespins moved using OSS control was greater than or equal to that of DC, Figure 6. These results validate the feasibility of the OSS HMI and show the potential for this application.

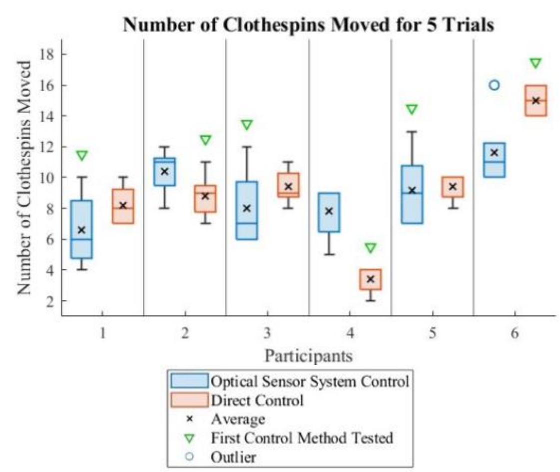


Figure 6: Boxplot of the Number of Clothespins Moved for 5 Trials.

IV. Limitations and Future Work

The short operating distance of the selected sensor is the major limitation of the design. During the movement of the forearm, the distance between the forearm skin and sensor often falls outside of the measurement range. When this happens, movement data is lost, which contributes to the sensor drift caused by accumulation of integration error. Although the recalibration function is introduced to mitigate the impact of the measurement drift, it is not intuitive to conduct and may not be suitable for other applications.

To overcome these limitations, several options are available: 1) adopting a sensor with a larger operating distance, such as PAA5100JE-Q: Optical Tracking Chip (PixArt, Taiwan) or PAT9130EW-TKMT: Optical Tracking Miniature Chip (PixArt, Taiwan); 2) adopting an adaptive filter to eliminate the sensor drift [27]; and 3) to zero the sensor when a line of contrasting color to the skin is in view, similar to how [28] detected a black line to create an encoder. Future work could also involve testing the OSS HMI for other HMI applications that utilize forearm rotation.

V. Conclusion

An innovative wearable OSS HMI that measures forearm rotation was developed. The OSS implemented one optical sensor and was mounted on a small orthosis, which minimized the obstructiveness and enabled easy don/doff. This wearable HMI allowed for intuitive motions to be used as an input to a machine. The OSS HMI was tested for the application of prosthetic wrist pronation/supination control, for able-bodied individuals. Despite the limitations, the OSS HMI was shown to be feasible for this application.

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