# Optical Fiber Angle Sensors for the PrHand Prosthesis: Development and Application in Grasp Types Recognition with Machine Learning

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*Abstract*—**This work presents the instrumentation of the PrHand upper-limb prosthesis with optical fiber sensors to measure the angle of the proximal interphalangeal joint. The angle sensors are based on bending-induced loss and are fabricated with polymer optical fiber (POF). The finger angle information is used in a k-Nearest Neighbor (k-NN) machine learning algorithm for grasp recognition. Four kinds of grasp are evaluated: hook grip, spherical grip, tripod pinch, and cylindrical grip, with three objects each. As mentioned in the algorithm validation, it is essential to note: The average accuracy was 92.81 %.**

*Index Terms*—**Angle sensor, k-NN, Machine learning, upper-limb prosthesis.**

## I. Introduction

The most common causes of limb loss are cerebrovascular problems and occupational accidents [1]. In 2018 around 59,000 amputations were performed in Brazil [2] and in 2019 it was estimated that there were more than 528,000 people with disabilities in their hands and legs in Colombia [3]. Also, it was predicted that around 30 million people did not have assistive devices in developing countries. Therefore, the interest in developing robotics hands has increased in the last years [4].

The main goal of robotic hands is to help improve users self-esteem and support activities of daily living [5]. These devices can be classified as humanoid hands, prosthetic hands, and research hands [6]. Humanoid hands aim to be as similar as possible to the human. In the case of hand prostheses the main focus is that their functionality is close as possible to the human hand. Finally, research on prostheses seeks that the aesthetic and functional parts have the most remarkable similarity to the human hand [7]. Generally, the prostheses are made with rigid and industrial mechanisms and heavy materials that increase the cost. Their performance is based on several motors and axes, making them more complex devices [8].

To overcome the disadvantages of traditional prostheses, a new line of prostheses is being investigated, with which the actuation mechanism is based on soft robotics. The advantages of this approach are the reduced costs, lightweight, increased functionality, and making the modules of the device elasticity more like the human body, improving the safety when using the device [9].

For monitoring the activity of the prosthesis and detecting external stimuli such as force and pressure, the use of sensors to monitor these variables is necessary. The commonly used sensors are accelerometers, onboard sensing to evaluate the choice of grasp, and strain gauges, among others [10], [11]. Since prostheses are based on rigid materials, the commonly used sensors have the same characteristic. However, for soft robotics-based prostheses, sensors coupled to their soft structure must be as flexible as possible to adapt to prostheses movements efficiently [10]. For that reason, optical fiber is taking place in the world of soft robotics, because one of its principal advantages is its flexibility, insensitivity to electromagnetic interference, low cost, lightweight and small dimensions [12].

The optical fiber is a medium through which light is propagated. Internally the light is reflected along the fiber to be transmitted from one side to the other. Optical fiber sensors have been included in several biomedical applications such as: monitoring the wrist [12], the fingers [13], the elbow and the ankle [14]. In prosthesis, some works related to sensing the pressure in the socket-user interface [15] and mapped the strain of a below-knee prosthesis [16].

PrHand is a hand prosthesis, described in [17], an electro-pneumatic device based on soft robotics and compliant mechanisms. The prototype and parts of the PrHand are presented in Fig. 1. It is a soft robotic prosthesis with elastic joints that extend fingers with an internal flexible tendon. On the other hand, finger flexion is performed with an inelastic tendon and a servomotor. For that each tendon goes from the fingertip to the unifying mechanism. Here all the inelastic tendons join and convert into the unifying tendon that goes to the servomotor. The fingers are based on a compliant mechanism

This work was partially supported by FAPES (209/2018 - Edital Especial CPID and 459/2021) and CNPq (310668/2021-2)

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allows them to have the degree of freedom (DOF) of flexion, extension, abduction, and adduction. For the abduction and adduction movements are used air-controlled silicone actuators are located between the fingers in the red points in Fig. 1. Another characteristic of the prosthesis is that it is underacted because it can control up to 15 DOF with one motor and one pump air. The fingers have silicone coatings to improve grasping by increasing the friction between the object and the fingers. The control is performed in Robot Operating System (ROS) on a Single Board Computer (SBC, Raspberry Pi 3).

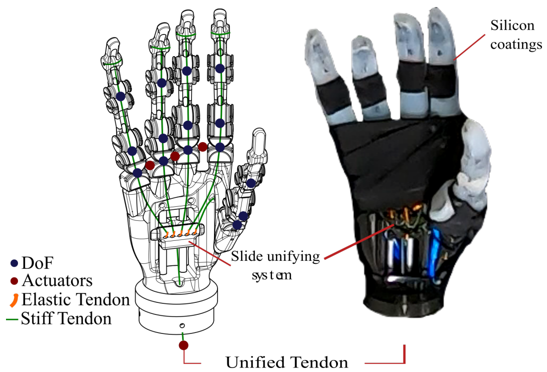


Fig. 1. PrHand prosthesis based on soft-robotics.

The main goal of this work is to report the development of a fiber optic angle sensor for angle measurement of the proximal interphalangeal joint in the PrHand prosthetic fingers. The developed sensor is based on optical power measurement, where the angle changes are related to the power losses during light transmission through the optical fiber. The angle information is used in the k-Nearest Neighbor (k-NN) classifier to recognize grasp kinds.

## II. Methodology

### A. Angle sensor and benchmark

A polymeric optical fiber (SH4001, Mitsubishi Chemical Co.) was used for sensor development, due to the aforementioned advantages including flexibility, impact resistance, and high deformation. The working principle of the sensor is based on intensity variation in transmission mode which means that optical power variations are measured considering a variation in the curvature of the fiber. A lateral cut creates a sensitive zone where there are power losses for better sensor sensitivity. The more the angle increases in the sensitive zone, the more bending losses are induced, leading to an attenuated signal in the photodetector. The length of the fiber, the length of the cut and the depth are factors that will influence the power variation [18]. A polymeric optical fiber (POF) curvature sensor is fabricated and anchored to measure the angle in the proximal interphalangeal joint of the fingers.

Six cycles of opening and closing the hand were performed per finger for the evaluation. Every 20 seconds the angle of the motor was changed by approximately 30° until the hand made a complete cycle of closed and opened. The voltage in the photodetector was measured with a microcontroller (Arduino Uno, Arduino, Italy). As a reference, a camera was used to record the open/close cycles and the Kinovea software tracked the changes in the finger angle.

### B. Data Processing for ML Algorithms

*1) Grasp types recognition protocol:* Considering the kind of grasp the human hand can do and the need to grasp objects in daily life activities, three objects were chosen to make the classification algorithm. The first is the hook grasp (H), where a skillet lid (H1), a cup (H2), and a pitcher base (H3) are used. The second is a spherical grip (SG), where three spheres of different diameters (75 mm (SG1), 96 mm (SG2), and 140 mm (SG3)) were selected. The third one is a tripod pinch (TP) with a large marker (TP1), a tuna can (TP2), and a golf ball (TP3). The last one is a cylindrical grip (CG) with a chip can (CG1), a chocolate can (CG2), and a tube (CG3). Fig. 2 shows the prosthesis grasping one object (SG1). As shown in Fig. 2, one fiber sensor for angle measurement border each finger, and the red parts are the sensitive zone (the light radiate out the fiber). To generate the database for the classification algorithm, the following protocol was proposed:

- The prosthetic hand is open
- Put the object over the prosthesis
- Close the prosthetic hand
- The prosthesis holds the object
- Open the prosthesis
- Remove the object
- The prosthetic hand is completely open again

All steps were made with all objects three times. For each step, 2500 samples of the angle sensor were taken.

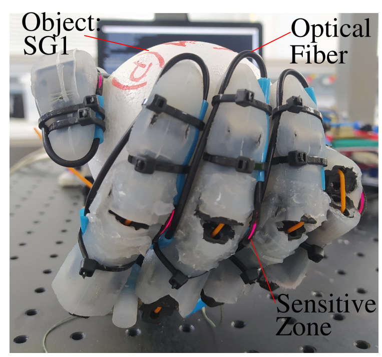


Fig. 2. PrHand grasping SG1 object of the protocol. It shows the optical fiber sensors and their sensitive zone.

*2) k-Nearest Neighbor (k-NN):* The Euclidean distance is used for calculating the distance between the testing sample and the training samples. The database is divided into two parts, the first one for training (30 %) and the second for testing (70 %). For calculating the k value, the training data was divided into two equal parts and proven with k= 1, 2, 3, 6, and 9. To evaluate the algorithm performance, the accuracy is calculated. The K-Fold Cross Validation was used to assess the algorithm better. Aleatory parts of the database (testing and training samples) were taken and was calculated the accuracy with each one. This process was performed ten times; considering previous studies have a low bias and modest variance with that number of repetitions [19].

## III. Results and Discussion

### A. Benchmark

The fingers characterization leads to the equations of Table I, where $A_c$ is angle close, $V_c$ is voltage close, $A_o$ is angle open, and $V_o$ is voltage close. Equations of line 1 describe little finger behaviour, line 2 ring finger, line 3 equations describe middle finger, line 4 index finger, and line 5 are the equations for the thumb. The results show a linear coefficient $R^2$ higher than 87 % for all fingers, implying an acceptable relationship between the angle and voltage changes. Two equations have been used for the open and close cycles since the curvature sensors show hysteresis in the worst cases with 4 %. Leal et al. have proposed techniques [20] to compensate the hysteresis and the viscoelastic effects .

TABLE I
Angle Voltage equations per finger

| Finger | Close hand | Open hand |
|---|---|---|
| **Little** | $V_c$=-0.0042$A_c$+4.8808 | $V_o$=-0.0045$A_o$+4.9131 |
| **Ring** | $V_c$=-0.0194$A_c$+2.3561 | $V_o$=-0.0217$A_o$+2.5834 |
| **Middle** | $V_c$=-0.006$A_c$+2.3778 | $V_o$=-0.0061$A_o$+2.4054 |
| **Index** | $V_c$=-0.0054$A_c$+4.6702 | $V_o$=-0.0043$A_o$+4.5757 |
| **Thumb** | $V_c$=-0.0357$A_c$+8.1344 | $V_o$=-0.0483$A_o$+9.9173 |

### B. Data Processing for ML Algorithm

One thousand samples were taken per repetition when the prosthesis was in step 4 of the protocol. The dataset consists of 36000 samples where 3000 were per object. Fig. 3 shows the Principal Components Analysis (PCA) graph per object of the database, each kind of grasp has a different marker. In most of the objects, there are differences between the others. In the case of the hook grip (diamond markers), and the cylindrical grip (square markers), their objects clustered in a concentrated region, and that was related to the position of the fingers is similar independently of the object shape. In both kinds of grip, all the fingers make the grasp. In cylindrical objects, the principal change will be how much the finger closes due to the diameter of the cylinder, and in hook the fingers are always almost close.

To validate the k-NN algorithm for the proposed approach, the data was divided into 30 % for training (10800 samples) and 70 % for testing (25200 samples). The k with better accuracy response was k=1. For that reason all tests were made with that k value. Table II are presented the k-NN results for each object. H1, H3, SG1, SG2, CG1, and CG2 are always classified in their corresponding groups, and it makes sense because the PCA (Fig. 3) shows that per object, the data is always in a region of the graphic. In the case of H2, TP1, TP2, and CG3 their distribution is more scattered, making them recognized as others.

Consedering that the same objects will not always be available, it will always be possible to classify them within a grip type. In that order of ideas, the database is divided by

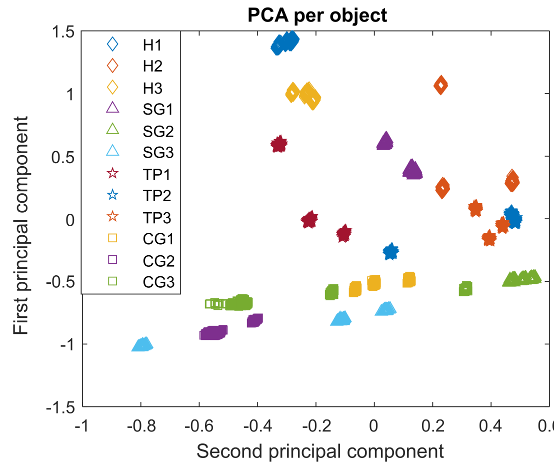


Fig. 3. Principal Components Analysis (PCA) for the angles sensors per object. The diamond is related to the objects of Hook grasp. The triangle is connected to the objects of spherical grip, the stars are tripod pinch objects, and the squares are the cylindrical grip objects.

grip type, joining the samples of the three objects by grip type. The accuracy results of the classifier by grip type are given in Table III. Although H2 has some percentage error in the hook grasp, its accuracy is 100 % because, at all times, the classification was always related to a hook object. The most complex to classify is the travel pinch; Table II confirms that information, specifically TP1, where its classification has a large error percentage in H3. This is related to the fact that it was a tiny object, so the fingers had to be closed almost entirely as in the hook-type grips. Even, in Fig. 3, it is seen that there is a group of TP1 that is close to H3. There is another considerable error percentage in the SG3 object with the object CG3, that was related to object geometry because both have circular forms in their structures. The average accuracy for all data is 92.81 $\pm$ 0.47 %, showing that a machine learning algorithm is a good alternative to classify those signals.

One study found in the literature about the use of ML algorithms for the perception of an upper-limb prosthesis, used angle sensors information for gesture, shape, weight, and size recognition; although they were tested with different algorithms, the k-NN had better accuracy [21]. In most of the other articles found, the information used for the algorithm was related to camera information [22], [23], which makes a system more expensive.

## IV. Conclusions

A fiber optical angle sensor for the PrHand hand prosthesis fingers was developed and characterized. The sensor is easy to fabricate, and its characteristics agree with the prosthesis soft robotics attributes due to the optical fiber flexibility. A linear relationship was found between the voltage and finger angles higher than 87 %. The angle information was used in the k-NN algorithm for grasp and object recognition. Regarding the grasp type, the achieved accuracy was higher than 85 %. However, the accuracy for object classification was lower.

TABLE II
K-NN ACCURACY PER OBJECT

| | | Prediction | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **H1** | **H2** | **H3** | **SG1** | **SG2** | **SG3** | **TP1** | **TP2** | **TP3** | **CG1** | **CG2** | **CG3** |
| **Real** | **H1** | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **H2** | 0.00 | 55.56 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **H3** | 0.00 | 44.44 | 100.00 | 0.00 | 0.00 | 0.00 | 44.44 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **SG1** | 0.00 | 0.00 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **SG2** | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **SG3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 64.44 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 4.44 |
| | **TP1** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 55.56 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **TP2** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 42.22 | 31.11 | 0.00 | 0.00 | 0.00 |
| | **TP3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 57.78 | 68.89 | 0.00 | 0.00 | 0.00 |
| | **CG1** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 8.89 | 0.00 | 0.00 | 0.00 | 100.00 | 0.00 | 26.67 |
| | **CG2** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 22.22 |
| | **CG3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 26.67 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 46.67 |

TABLE III
K-NN ACCURACY PER KIND OF GRASP

| | | Prediction | | | |
|---|---|---|---|---|---|
| | | **H** | **SG** | **TP** | **CG** |
| **Real** | **H** | 100.00 | 0.00 | 14.81 | 0.00 |
| | **SG** | 0.00 | 88.15 | 0.00 | 1.48 |
| | **TP** | 0.00 | 0.00 | 85.19 | 0.00 |
| | **CG** | 0.00 | 11.85 | 0.00 | 98.52 |

Some objects were classified correctly with 100 % accuracy, and others were classified with lower accuracy but shared the same type of grasp. In future work, it is proposed to complement the angle information with pressure sensors in the fingers and, in that way, improve the grasp recognition. In addition, the sensor hysteresis will be reduced by applying some of the techniques reported in the literature. The angle sensor will be optimized using another kind of fiber to house the sensors inside the fingers.

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