

Sensor evaluation for hand grip strength

Soly Mathew Biju, Hashir Zahid Sheikh

Faculty of Engineering and Information Sciences, University of Wollongong in Dubai, Dubai, United Arab Emirates

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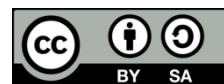
Hand grip strength

Sensor device

ABSTRACT

This paper discusses the evaluation of the sensors used in the hand grip strength glove. The glove comprises of flex and force resisting sensors. Force resisting sensor determines the force applied by various parts of the palm, while the flex sensor determines the flexion of the fingers. These sensors are placed in a specific position on the glove to obtain correct data when the glove is used. The glove has two modes, which are pencil grip mode and object grip mode. The sensors determine which mode the glove is in depending on the gesture made. The glove is examined using a pencil and a cylindrical object to evaluate the strength of the grip. After gripping the object or pencil, the system evaluates the force applied using the sensors. This data is transferred to a computer for further analysis using a trained model. The model was able to achieve an accuracy of 90.8%.

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Corresponding Author:

Soly Mathew Biju

Faculty of Engineering and Information Sciences, University of Wollongong in Dubai

UOWD Building, Dubai Knowledge Park, Dubai, United Arab Emirates

Email: solymathewbiju@uowdubai.ac.ae

1. INTRODUCTION

Sensors are widely used in many applications. One such use of this is in gloves. These gloves take data from the sensors and forwards it to the system. The system would then determine what it should do with this data. Prior to the beginning of 21st century, the estimation of power applied by the hand were limited because of technological limitations. The present situation has changed with the headway of the ultrathin sensors.

Tarchanidis and Lygouras [1] proposed a glove that consists of flex sensors and strain gauge force sensor to evaluate the power applied. To check the glove, a ball was pressed to assess the power applied. This framework lacks in estimating the power applied by tip of the fingers and the force applied by the palm. To make the glove more accurate the glove had a non-stretchable support around the fingers. Flex sensors utilized in this test have serious degree of error, which makes the force calculated inaccurate. Du *et al.* [2] proposed a mechanical methodology to compute the power applied by the hand. Voltage is generated using the angle sensor when they are rotated. Furthermore, displacement sensors create voltage when the cylinder is dislodged, the cylinder has a magnetic ring around it. The outcomes showed that a limit of 47 N could be registered by the framework. This framework has serious level of error because of the contribution of friction in the glove. Also, the glove is quite heavy, which makes it harder to assess the power. As a portion of the power is needed to hold the glove [3].

Lee *et al.* [4] recommended a way to deal with the tip force applied by fingers called grip force glove measurement system. It was intended to quantify the power applied on muscles and joints. To evaluate the results of the grip framework, members were given long round and hollow handles with various distances across. The outcomes showed that thumb applied the most power, while ring and middle finger applied high power. Additionally, this paper needs more information to assess the implementation of the grip force glove.

It requires an interface to show the power being applied which is simpler to understand. Another paper suggested a hand restoration framework in [5] which comprises of force sensitive resistor (FSR) sensors and flex sensors to decide the flexion of the fingers and power applied by the tips of the fingers. To decide the effectiveness of the glove, an elastic ball was pressed while wearing the glove. The flexion of fingers and power applied by the fingers, will be determined with the help of the glove. Bustamante *et al.* [6] offered a sensor glove-which comprises of FSR sensors to support in finding Parkinson illness and amyotrophic lateral sclerosis (ALS) in patients. To decide the proficiency of the gloves, finger tapping, and hand grip tests were performed on it [7], [8]. A reasonable smart glove was proposed by Akpa *et al.* [9]. To assess the function of the glove, the client needs to wear it and use it during workouts. The glove was able to evaluate which exercise is being played using by the power applied from the FSR sensors. The framework accomplished a precision of 87%.

Another research by Nabilah *et al.* [10] made a wired glove framework called GloveMAP. To evaluate the glove, the glove was tested using bottles with different weights. Information was extracted from the glove by connecting it to the personal computer (PC). The information was exhibited on diagrams to show how much power each finger is applying. Nevertheless, this plan needs legitimate assessment of the power applied by the hand. It just measures the power applied from thumb, first and second fingers. This glove requires more sensors to get more exact information. Particularly around the palm and other fingers to know their commitment in grasping of the object. Similar framework was utilized in [11], [12] to evaluate the tripod grip intensity. The framework had the option to arrive at precision of 90% in assessing the grip strength. Yap *et al.* [13] suggested a smart glove that utilizes flex sensors and FSR sensors for post stroke hand treatment. To assess the glove, an elastic ball was pressed with various measure of powers.

Nageshwar *et al.* [14] aligned a FSR sensor. To align the FSR, recognized loads were put on the FSR and readings of current were captured. This information is utilized to make an alignment bend using the current and real power applied by the loads because of gravity. The outcomes showed the level of error made by the sensor. Machine learning is developing the precision and swiftness of the framework in [15]. Pushpa *et al.* [16] machine learning was utilized to inspect the execution of a class. They made examples from past outcomes to gauge the following outcome random forest classifier was the most exact model in estimating. Krishnamurthy *et al.* [17] proposed a framework MALADY. It utilized the information from sensor to grasp and settle on decisions continuously. Henceforth, this made the framework self-sufficient. The prototype was made by utilizing an support vector machine (SVM) based classifier [18]–[21]. Machine learning was additionally used to help fall identification in [22]. It utilized information from wearable device to anticipate the fall and its heading with the aid of artificial intelligence (AI). The outcomes were very precise and had the option to perceive fall. Additionally, hand signals were perceived by utilizing AI in [23], [24]. Neural networks were utilized to help in deciding a specific motion, six signals were utilized to test the framework.

The glove discussed in this paper uses force resistive sensors and flex sensors. The glove has two different modes to determine the grip, which are pencil grip strength and object grip strength. This glove would tell the user in real-time the grip strength of the user, if its weak or strong. Most of the papers mention in this literature review had FSR sensors to measure the force applied by the user. However, there were some papers which used flex and FSR sensors together. For example, in studies [5], [25] same sensors are used, but the placement and the methodology are quite different. The machine learning applied on the glove sets it apart from any other research. Moreover, the ability to switch between the two modes automatically is icing on the cake [26]. The pencil grip mode is not discussed in these papers, which makes this glove unique.

The rest of the paper is arranged as following. An in-depth method section, which discusses the methods that were used. A section for findings is also included to evaluate the outcome of these procedure. Finally, a conclusion to review the outcomes in this paper.

2. METHOD

2.1. Selection of sensors

2.1.1. Flexion of fingers

For the flexion of fingers, they are variety of sensors that can be used. One method that could be used is a potentiometer with a cable, the potentiometer will tell the user how much cable has been pulled. The pull of the cable will be converted into resistance, this would be used to determine the flexion of the fingers. However, this method is too bulky and inefficient. Another method could be to use a flex sensor that could measure the bending of the fingers. This method is quite light when compared to the potentiometer one. Hence, flex sensor seems to be the better option here.

2.1.2. Force applied by hand

For the fingertips, a sensor is required that can measure the force applied by the fingertips. There are many sensors that could such as load sensor, FSR sensor and two sheets of copper separated by foam. Load

sensor is quite heavy and impractical for this system. This will make the glove heavy and might constrict movement. FSR sensor are light weight and can work in this scenario, since lot of these sensors would be used. Two sheets of copper separated by foam is a novel method to form a force sensing sensor. However, this could have large inconsistencies. Moreover, this sensor has a larger surface area when compared with FSR sensors. Hence, FSR sensor seems to be the better option here.

The force sensitive resistor (FSR) was connected with the Arduino and resistor to determine its raw value. One pin of the sensor was connected to a resistor with resistance of 10 k Ω which was also connected to an analog pin, while the other pin of the sensor was connected to 5 V. The other end of the resistor was connected to ground. Force resistive sensor connections are shown in Figure 1.

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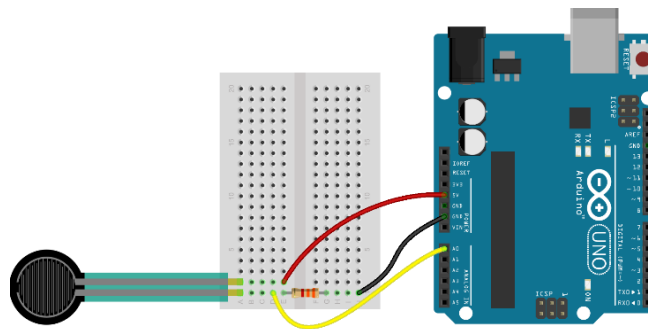


Figure 1. Connections for FSR sensor

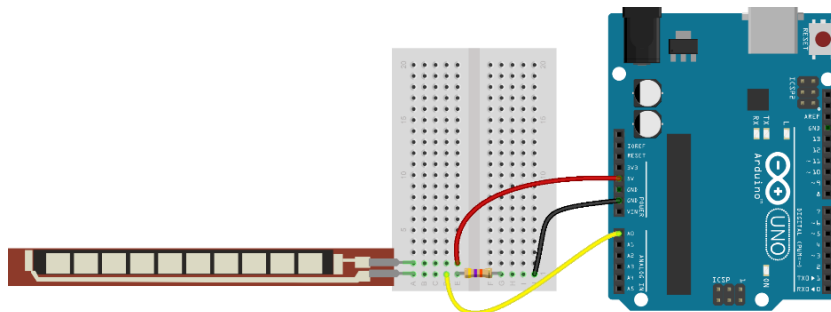


Figure 2. Connections for flex sensor

2.2. Calibration of sensors

2.2.1. Force resisting sensor

To calibrate the sensors, the Arduino was programmed. The Arduino code was modified so that it can get the correct weight in Newtons. To verify the calibration, multiple weights were used. The weights consist of 0.5 kg, 0.7 kg and 0.9 kg. However, the base area of these weights was bigger than the surface area of the FSR sensor. To overcome this, a small weight of 20 g was used. This weight was able to fit on the surface area of the FSR sensor. The other weights were placed on this, so the pressure was transmitted to the FSR surface area. The readings were noted down and the code was tweaked until the microcontroller showed the same weights as the weights were used.

2.2.1. Flex sensor

To calibrate the flex sensors, the Arduino was programmed. The Arduino code was modified so that it can get the twist in degree that was mapped from resistance. To verify the calibration, two points were used. These two points were 0 degree and 90 degrees. To map these resistances, we used these two points. And then the other values are computed using this map function.

After the mapping was done, certain things were observed. To hold an object, angle of 13 degrees or more is required. This was also used to determine the mode the user is in. For pencil mode, the user had to use first two fingers and the thumb. If these sensors showed a value greater than 13 that means it is in pencil mode. For the object mode, four fingers and thumb are required to register a reading of 13 degree or more. This was also used to evaluate the flexion of the fingers. This can show if the fingers can bend properly or not. To test this condition, the person has to make a fist. When the person makes a fist, the sensors register a reading of 60 degrees or more.

2.2.3. Placement of the sensors

The position of the sensors is a very crucial part of this experiment. Flex sensors can only be placed where there is bending. So, the most obvious place would be to place them on the top of the fingers and thumb, however it could also be placed inside. But since we need to place FSR sensors as well, it is better to place them above the fingers to avoid any inaccuracies in the readings. For the FSR sensors, it can be placed on the fingertips to get the force exerted by these points. This could be very useful for pencil mode. Moreover, FSR sensors need to be placed on the palm too. This would be crucial in holding an object or being in object mode. To get the points on the palm, various test needs to be performed. Like holding the object while the FSR is placed in different places. And then register the highest readings and location of these readings.

2.2.4. Generating and classifying data

The data from the sensor is printed on the serial node using Arduino microcontroller. The data is separated by a comma and prints all the FSR sensors first, followed by the flex sensors. Using the flex sensor values the program determines which mode the user is in. If the first two fingers and thumb are gripped the system determines the mode as P which is pencil grip. If all the fingers and thumb are gripped the system determines the mode as O which is object grip. The program also classifies the data based on the average force applied by the fingers. The data is classified first into categories that are L (weak) and H (strong). The mode and the class are also printed on the node. The Arduino code is attached in the appendix.

2.2.5. Machine learning program

The csv file is processed by an SVM based machine learning program to classify the data. The data is classified first into categories that are L (weak) and H (strong). And then the program is trained using this manually classified data. The data was divided into training data and test data. The test data was 25% of the whole data.

3. RESULTS AND DISCUSSION

3.1. Force resisting sensor

Figure 3 shows the weight that was applied on the FSR along with 10 g weight to exert all the weight on the force sensing region. The reading on the serial monitor was 0.51 kg. Weight of 700 g was placed on the FSR along with 10 g weight to exert all the weight on the force sensing region as shown in Figure 3. The reading on the serial monitor was 0.71 kg. And then weight of 900 g was placed on the FSR along with 10 g weight to exert all the weight on the force sensing region as shown in Figure 3. The reading on the serial monitor was 0.91 kg.



Figure 3. 500 g weight on FSR

3.2. Flex sensor

Figure 4 shows the angle of the bending and resistance of the flex sensor at stationary value or 0 degrees. The reading on the serial monitor was 1 degree. The flex sensor was then bent at 70° similar to Figure 4. The reading on the serial monitor was 72°. The flex sensor had a maximum of 82° when the fingers were close to the palm. This test was used to determine the flexibility of the fingers.

However, for testing the two modes the sensor needs to show a change in angle by 60°. The mode is decided based on the angles generated from each finger. If the first two fingers and the thumb produce an angle of 60° or more, the mode is pencil grip. If more fingers create an angle of more than 60° the system is in object mode.

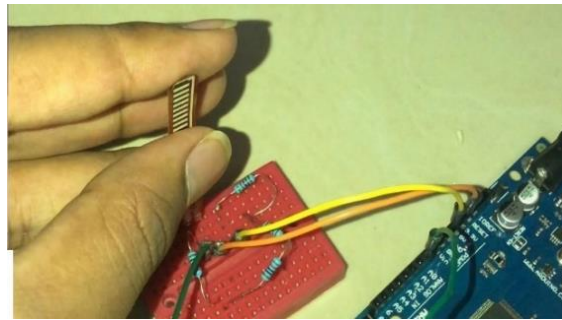


Figure 4. Flex sensor reading at 0 degree

3.3. Placement of the sensors

Figure 5 shows the placement of the force resisting sensors on the hand. They are placed at the tip of the hand to get the force exerted by the finger. The rest four are placed on the palm. This design is made in consideration of the application that are holding an object or a pencil. Figure 6 shows the placement of the flex sensors, they are placed on top of each finger and thumb. They are going to be used to determine the bending of the fingers using the change in resistance from the flex sensors. This design was made in this way to avoid conflicts between the FSR and flex sensors.

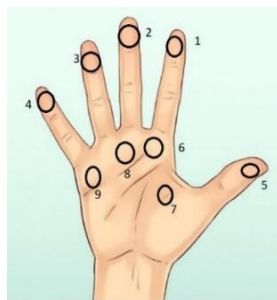


Figure 5. Placement of FSR



Figure 6. Placement of flex sensor

3.4. Generating and classifying data

The serial node is read by another application and then stored in a CSV file. The program starts saving the data when the port is selected and saves the file when the save button is clicked. The first nine readings are from FSR sensors, the next five readings are from flex sensors. The mode is determined using the flex sensor and then the data is classified using the values from FSR sensors. Figure 7 shows the outcome of the program.

3.5. Machine learning program

After training the classifier using 75% of the data, the classifier was tested using the test data. The Figure 8 shows the outcome of the trained program. The value of the accuracy also varies depending on which mode the glove is in. the pencil grip mode has more accuracy as compared to object mode.

0.43,0.09,0,0,0,0.48,0,0.94,0,49.00,67.00,37.00,45.00,31.00,0,M
 0.42,0.10,0,0,0,0.50,0,0.94,0,48.00,67.00,37.00,45.00,30.00,0,M
 0.40,0.09,0,0,0,0.50,0,0.93,0,51.00,67.00,38.00,46.00,31.00,0,M
 0.38,0.08,0,0,0,0.50,0,0.93,0,47.00,67.00,36.00,45.00,30.00,0,M

Figure 7. Serial node output

	FSR 1	FSR 2	FSR 3	FSR 4	...	Flex 5	mode	outcome	Predictions
1875	3.38	0.94	0	0.21	...	75	O	H	H
607	0.00	0.00	0	0.00	...	-14	P	H	H
1432	0.00	0.00	0	0.00	...	-12	P	H	H
569	0.00	0.00	0	0.00	...	-14	P	H	H
1213	0.00	0.00	0	0.00	...	-12	P	H	H
...
1363	0.00	0.00	0	0.00	...	-13	P	H	H
627	0.00	0.00	0	0.00	...	-14	P	H	H
281	0.00	0.00	0	0.00	...	-13	P	L	L
672	0.00	0.00	0	0.00	...	-14	P	H	H
2015	3.53	1.11	0	0.42	...	63	O	H	H

Figure 8. SVM program output

The confusion matrix in Table 1 shows the outcomes of the SVM program, it shows that the system has an accuracy of 90.8%. L means that the grip is weak while H means that its strong. As the table show that the glove can detect strong grip effectively. There is only some issue in weak grip which can be fixed with more data.

The box plot in Figure 9 shows the difference of force applied by the hand while holding a pencil. The force applied is the average force applied by the first finger, second finger and thumb. The weak grip was mostly in the range of 1.1 and 1.45. The strong grip was in the range of 5.95 to 8.0, which shows the strong grip had more range difference than the weak. More data can aid in providing better results, especially for weak grip.

The box plot in Figure 10 shows the difference of force applied by the hand while holding an object. The force applied is the average force applied by all the fingers and thumb. The weak grip was mostly in the range of 0.03 and 0.06. The strong grip was in the range of 1.2 to 1.95, which shows the strong grip had more range difference than the weak. More data can help in providing improved results, especially for weak grip.

Table 1. SVM confusion matrix

	Actual Class	
	L	H
Predicted Class L	1174	0
Predicted Class H	195	760

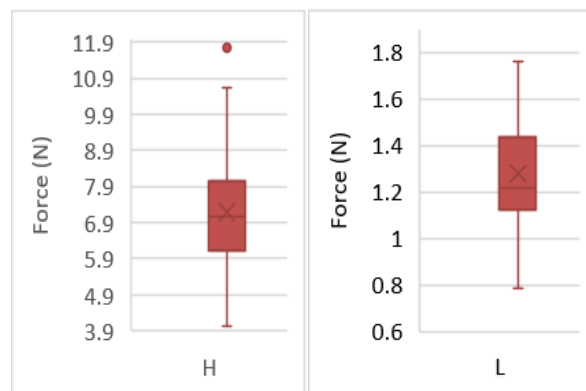


Figure 9. Boxplot for pencil grip

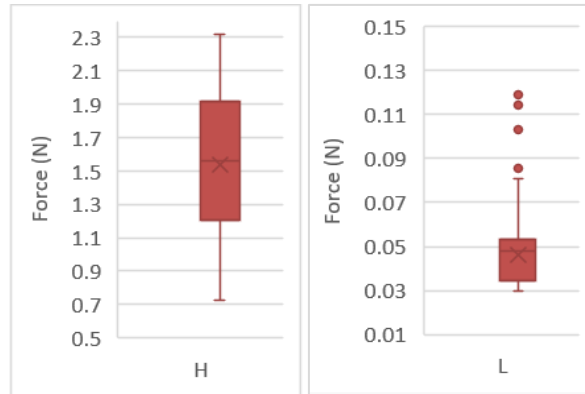


Figure 10. Boxplot for object grip

To see the comparison between the two modes a scatterplot was obtained, that is shown in Figure 11. The two areas on the hand that are covered are the palm and the fingertips. In pencil mode most of the force was applied by the fingertips, while in object grip most of the force was applied by the palm. The interesting outcome from these two modes is that the fingertips had a significant difference in forces when compared to force applied by palm. This could be due to the surface area of the palm is more than the surface area of fingertips.

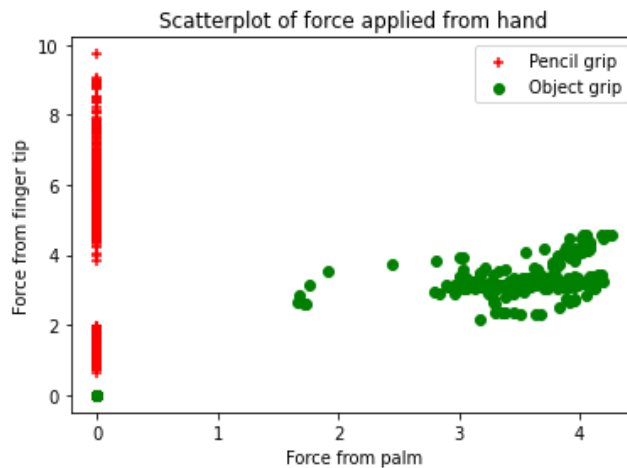


Figure 11. Scatterplot for force applied by object and pencil grip

3.6. Discussion

The proposed solution in this paper is quite accurate due to the machine learning that is applied on the data. However, there are other reasons for this accuracy too. The sensor selection in this research is key variable. The two sensors used are flex and FSR. FSR sensors are used to measure the force applied by the part of the hand, while the flex sensors are used to determine the flexion of the fingers and the mode the user is in.

Other important factor is the placement of the sensors. The FSR sensors are placed on the hand in such a way that it exhibits force applied by the hand on the object. These points are important to know, as wrong placement can cause errors in the evaluation of the glove.

Data classification for preparing the model is also a factor, as this helps to shape the prototype. This data needs to be classified properly as it is the benchmark used by the model to determine the grip strength. To make sure the classification is accurate, the flex sensors were mapped on to angles while the force applied by the FSR sensors were converted to force in newtons.

Machine learning is responsible for using the data and determining the strength of the user. This uses various factors like the grip mode and sensor data to determine if the user has a strong grip or not. The

major drawback in this glove are the wires used, the wires make the glove too heavy for use. Moreover, the wires can cause difficulty when the fingers are moved. The other drawback could be that there is not sufficient data to generalize the model for everyone.

A lot of work can be done on this glove to optimize its performance. The major upgrade would be to add wireless feature, which can make the glove easier to use. Moreover, unsupervised learning model can make the glove more accurate. More options can be added to the glove that can help in data classification. Features like age and gender can have a major impact in the detection of hand grip strength. However, this solution is very tough to implement practically.

4. CONCLUSION

This paper discusses the sensors used for a hand grip strength experiment. The aim of the experiment is to decide the strength of the grip by using flex and FSR sensors. Sensor placement was also another key variable of this experiment. After the sensor gets the data, it is analyzed by the machine learning model. The model is created by manually classifying the data. This prototype will then identify the grip strength and the mode the user is in. This model achieved an accuracy of 90.8%.

The major obstacle from this experiment is to detect the weak grip. The weak grip range is quite small which creates a problem in determining the weak grip. However, this can be resolved by adding more data from people with weak grip strength. Additional features like wireless feature, unsupervised model, age, and gender can be added to the glove to make it more robust. However, this would require more testing and data to verify the effectiveness of the system. It would be harder to implement, as it is harder to get more people to experiment and to differentiate the data extracted from the people.




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BIOGRAPHIES OF AUTHORS



Soly Mathew Biju    is an associate professor at the University of Wollongong in Dubai. She has over 21 years of work experience in academia and IT industry. Her research interests are in Machine learning, sensors applications, IoT and AI application in designing systems. She is a chartered engineer and fellow higher education academy. She is also holding mastery in IBM certified IBM AI analyst, IBM IoT cloud developer, security intelligence engineer, and IBM cloud application developer. She can be contacted at email: solymathewbiju@uowdubai.ac.ae



Hashir Zahid Sheikh    received the B.E. degree in computer engineering from University of Wollongong in Dubai, Dubai, United Arab Emirates, in 2019. He is a computer engineer at AppsPro. Current research interests' robotic systems, machine learning, IoT and communication. Previously worked on Implementation of a sustainable and scalable vertical micro-farm. He can be contacted at email: hashir9581@hotmail.com.