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The challenges of hand gesture recognition using dielectric elastomer sensors

Derek W. Orbaugh Antillon, Christopher Walker, Samuel Rosset and Iain. A. Anderson
Biomeimetics Laboratory, Auckland Bioengineering Institute, Auckland, New Zealand

ABSTRACT

Hand gesture recognition algorithms require information from the material world to be converted to digital data. In this paper we present an analysis of dielectric elastomer sensors for hand gesture recognition. A glove with five dielectric elastomer sensors has been used to collect motion data from the hand. The capacitance value of each sensor was read and analysed for a total of 24 participants. The study shows that the sensors provide enough information to differentiate gestures from each participant, although the maximum capacitance value varied with each participant, making gesture recognition over all participants difficult. Data processing allowed for this problem to be solved.

Keywords: dielectric elastomer sensors, strain sensors, motion gesture recognition, hand gesture recognition

1. INTRODUCTION

Humans use hand gestures in their day to day life as means of non-verbal communication. When interacting with one another, we perform gestures that range from something as simple as pointing to an object to something as complex as the expression of feelings or ideas [3]. Although gestures can be complex and dynamic, interpreting a hand gesture starts with differentiating simple static hand gestures.

Gesture recognition has been a topic of research since the development of enabling technologies such as accelerometers, motion sensors, infrared cameras, bend-sensors and vision tracking [1]. Gesture recognition refers to the analysis of human motion data to classify a specific gesture. It can be divided into three main groups: vision-based, motion-based and EMG-based. Vision-based recognition is when cameras and image processing algorithms are implemented to recognize gestures. Motion-based systems use a range of sensors attached to the body to convert movement into electrical signals, which are then processed to recognize gestures. These systems can be cumbersome and hinder the movement of the user, if the electrical and mechanical design is not well developed. EMG-gesture recognition requires the user to wear devices on the body capable of measuring electrical activity in the muscles, which is then processed to recognize the gestures. It has the advantage of being a hands-free system [2].

So, what gesture recognition technique is best for recognizing gestures? There is no correct answer to this question. It largely depends on the application where gestures are being performed. In this study, we are developing a gesture recognition system, which will enhance diver experiences during a dive. We aim to develop a system for underwater diver-to-diver or underwater diver-to-AUV communication. Vision cameras and EMG sensors are not suitable for all underwater environments,

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which is why we investigated a motion-based system. Specifically speaking, a hand gesture recognizing glove. In order to develop this glove, we first have to look at how to collect motion data.

Data gloves are wearable devices that measure joint angles, hand orientation and/or position in a 3D space. They consist of an array of sensors, electronics for data acquisition/processing and a power source [3]. Data gloves have been in development since the 1970s, but it wasn't until 1987 with the development of a product called "Data Glove", that data gloves started to be commercialized. This glove was brought to the market by Visual Programming Language Research. It had the novelty of being a multipurpose device, which used fibre optics for the joint angle measurements [4].

Similar gloves to the Data Glove were developed as general-purpose devices, but they all had the same drawbacks, namely, that the cumbersome electronics acted as a constraint on the user's hand and that the user-specific calibration method was tedious. Different designs were developed to overcome these weaknesses [4]. There are various data gloves available for purchase now, but because of their high cost, they are usually bought for research purposes or for special performances [5].

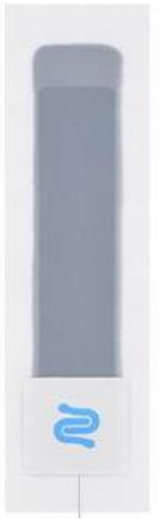
These gloves capture motion data using sensors, which can be inertial, magnetic or strain sensors. We have studied the performance of dielectric elastomer sensors for capturing this motion, because they are cost-effective, can be easily fabricated and are robust. They are also flexible and stretchable, which allows for them to move freely and not hinder joint movement. We analysed the data to determine its potential in hand gesture recognition and the robustness of a glove fabricated with these sensors. This is important, since hand gesture motion recognition has to deal with the problem that people have different hand sizes and ways of performing a gesture. Making a glove for every user would be impractical and costly.

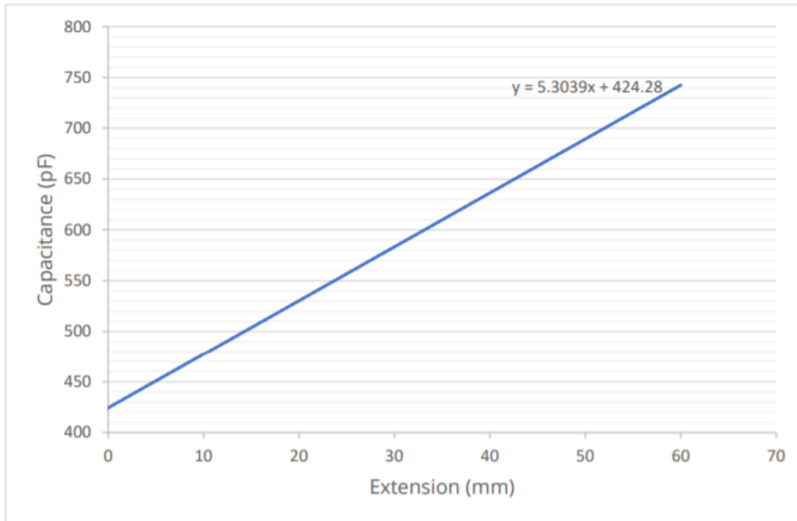
In this paper, hardware development (both DE sensors and measurement electronics) is presented in Section 2 with the experiments and methods outlined in Section 3. Finally the results and discussion are presented in Section 4.

2. HARDWARE DESIGN

a) Dielectric elastomer sensor

The sensor that was implemented in this study is the StretchSense strain sensor (Figure 1a). This sensor changes its capacitive value linearly with strain as shown in Figure 1b. It is a soft and flexible sensor that comes bonded to a white fabric, which allows for it to be integrated into wearable garments easily [32].





(a) (b)

Figure 1. a) StretchSense stretch sensor. b) StretchSense stretch sensor capacitive vs extension linear fit [32]

b) Glove design

Five of these sensors were integrated into a glove, one for each finger. The electronics to collect the data consisted in a 10 channel sensing circuit sold by StretchSense and a ProMicro microcontroller which was connected to the computer via a USB to micro-USB cable. The electronics were enclosed in a 3D printed box, which was sown to the glove as shown in Figure 2.

Figure 2. Experiment Glove

3. COLLECTING SENSOR DATA

Data was collected by having participants perform a range of gestures while sensor data was being collected. The experiment overview had three stages: setup, gesture performance and the end stage (Figure 3). In the setup stage the participants hand height, span and width were measured. Calibration of the sensors was also done in this stage. This process consisted of making a fist and transitioning to an open palm, which allowed for the initial maximum and minimum capacitance readings of each sensor to be established. The gesture performance stage consisted in having the participant sit in front of a computer and perform a range of gestures. The participant would have 5 seconds to perform the gesture correctly and would then hold it for 12 seconds. During this 12 seconds, 20 samples were taken. Each sample consisted of the maximum and minimum capacitances, as well as the actual sensor capacitance readings. This process was done for a total of 13 gestures. The experiment ended after the 13 gestures, where the data was saved and the glove was removed.

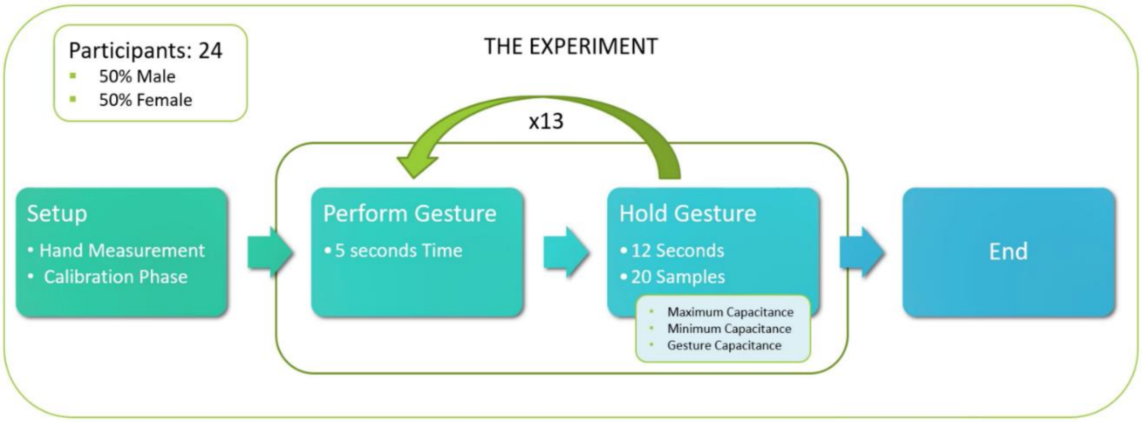
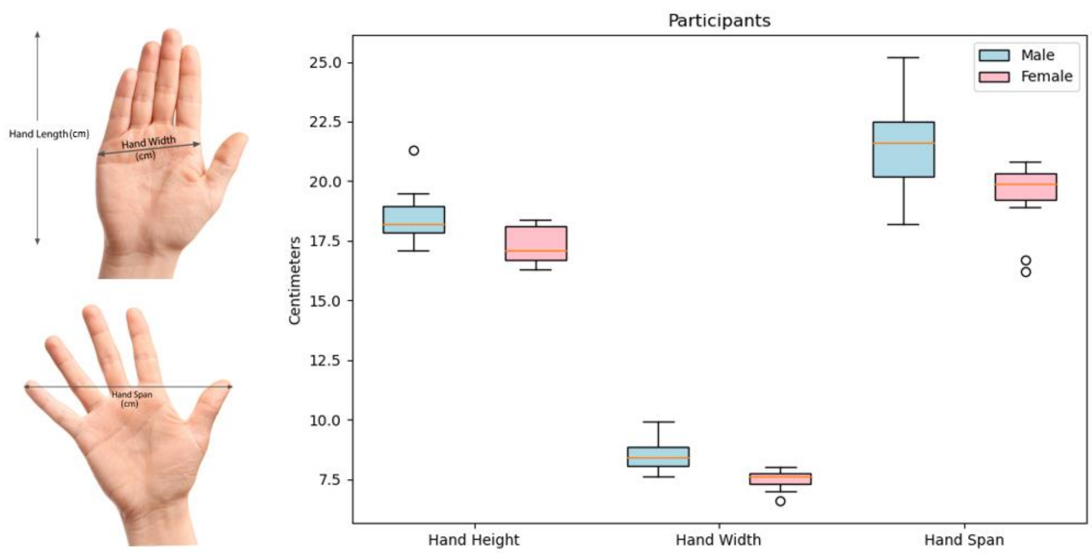


Figure 3. Data collection experiment overview

A total of 24 people participated in the experiment. Male and female participants were chosen evenly. As mentioned previously, the participants right hand was measured. Figure 4a shows the features that were measured. In Figure 4b we can see these measurements plotted. It can be seen that there is an acceptable distribution between the participants hand size.



(a) (b)

Figure 4. a) Hand features that were measured (hand length, hand width and hand span). b) Boxplot showing measurements for male and female participants

As described earlier, a total of thirteen gestures were performed during the experiment. These gestures are shown in Figure 5. They were chosen for the experiment based on the fact that most of them are used as diving hand signals and future work will consist of implementing hand gesture recognition in an underwater diving scenario.

Figure 5. Gestures analyzed in the experiment.

4. RESULTS

Here we show the analysis of the data that was collected. First, we have a look at the gesture data form an individual participant. This data is then compared with the data from a second participant and finally with all participants. Analysis of this data shows that sensor readings can be processed for gesture differentiation for individual participants, but once the data from many participants is merged together, gesture differentiation becomes less evident. The data from the sensors is then analyzed at the limits of the strain in correlation with the hands. Analysis of this correlation shows that the bigger the hand, the more the sensors are stretched, which leads to higher maximum capacitance values.

Figure 6 shows the capacitance readings of all five sensors for one participant. It can be seen that for each gesture the capacitance values of each finger are almost constant. When the gesture changes, so does the capacitance of the fingers that changed. Different gestures show low capacitance readings for fingers that are straight and high readings for those that are bent. This variation in the values allows for gestures to be differentiated.

Looking at the data of two participants (Figure 7) or of all participants (Figure 8), we can see that the capacitance readings vary significantly when the fingers are bent, for example when the gesture “four” is being held. We can see that for the index, middle, ring and pinky fingers the capacitance readings are very close to each other, but for the thumb, there is a big variance in the values.

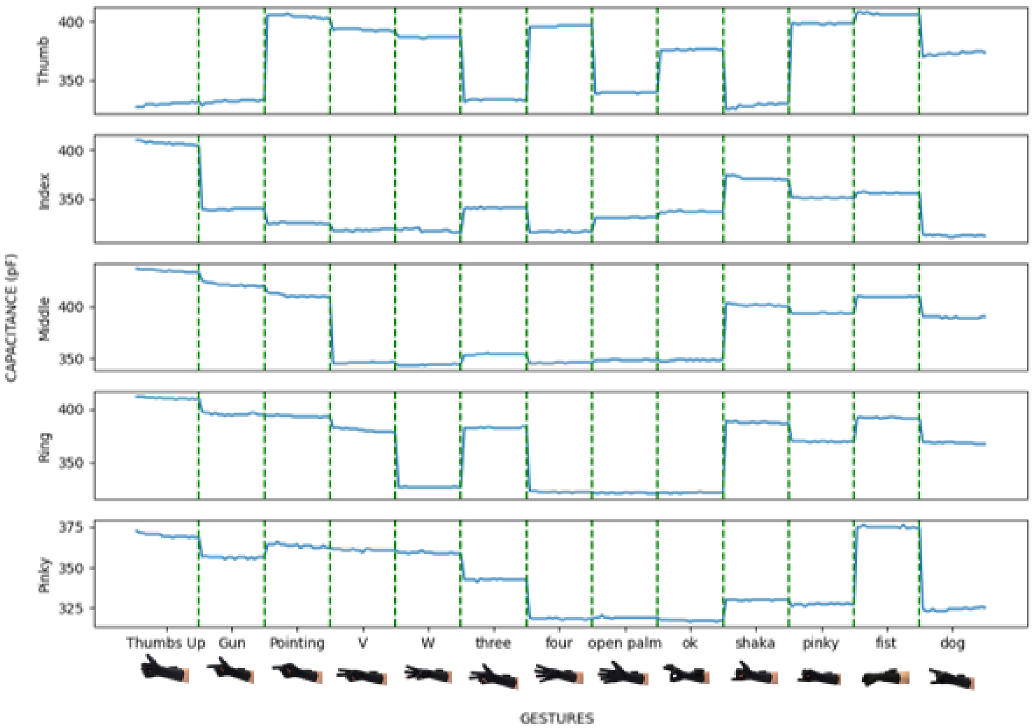


Figure 6. Capacitance readings of one participant vs the gestures being performed over time

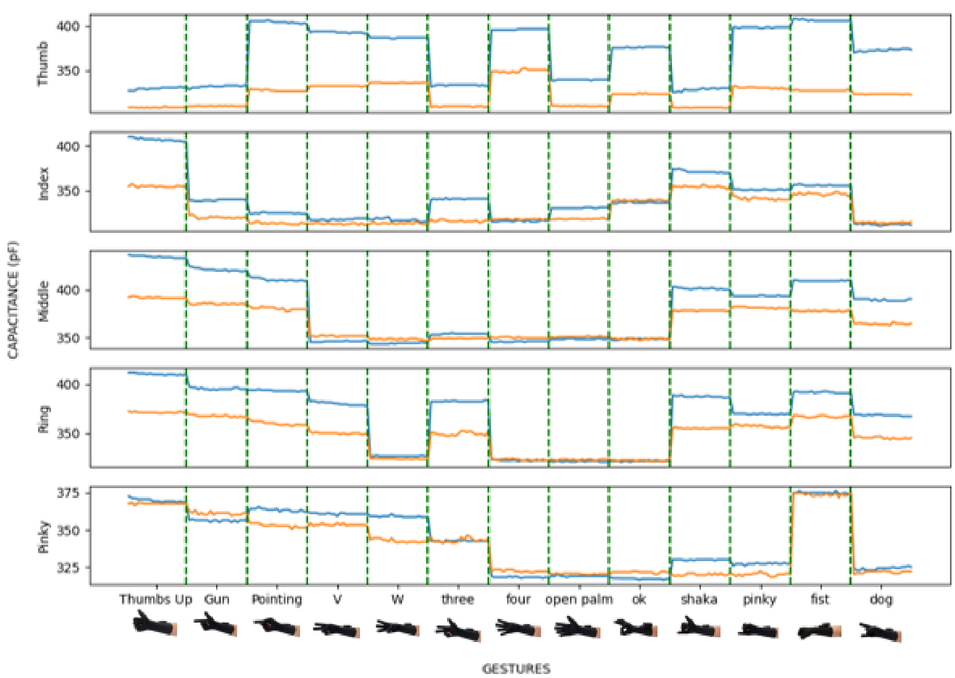


Figure 7. Capacitance readings of two participants (blue and orange) vs the gestures being performed over time

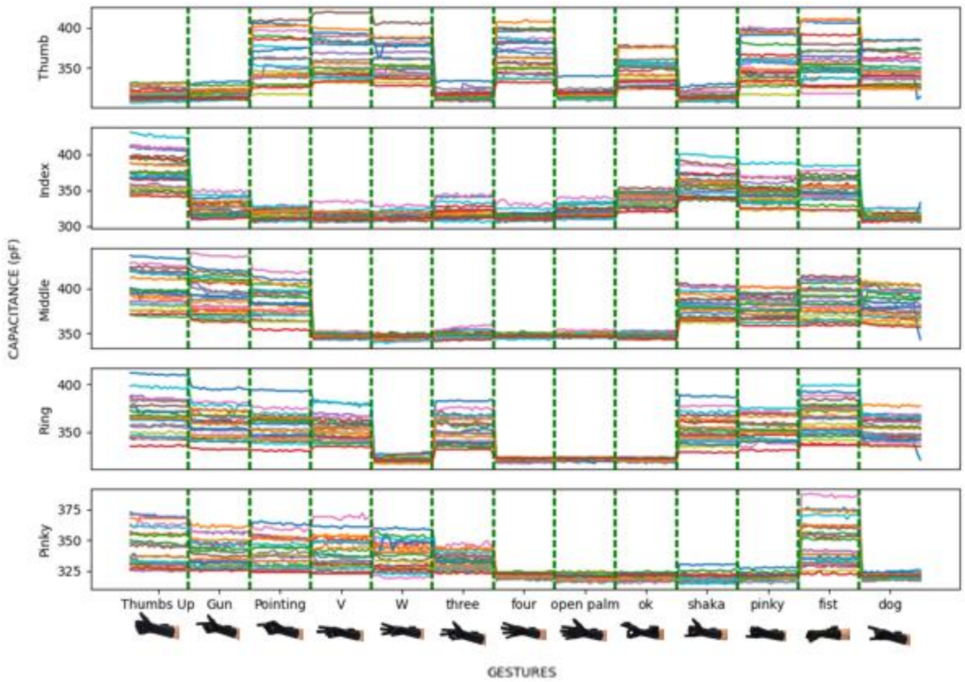


Figure 8. Capacitance readings of all participants vs the gestures being performed over time

The variance observed when the sensors are stretched raises the question if the dielectric elastomer sensor are adequate for gesture recognition over different users. We decided to look at the data of all participants and plotted the maximum and minimum capacitance readings. Figure 9 shows this data using boxplots. It can be seen that the minimum value, that is when the sensors are not stretched, the readings are similar for all participants. On the other hand, the maximum capacitance values vary significantly. So, what is the reason for this variance? We plotted the maximum capacitance with respect to the participants' hand's height, width and span. Figure 10 show this data for the index finger. The same trend is observed for the other fingers. It can be seen that there is some linear relationship between the maximum readings and the participants' hand size. This relationship is because the bigger the hand, the more the sensors are stretched when the fingers are bent, and thus the maximum capacitance readings increase.

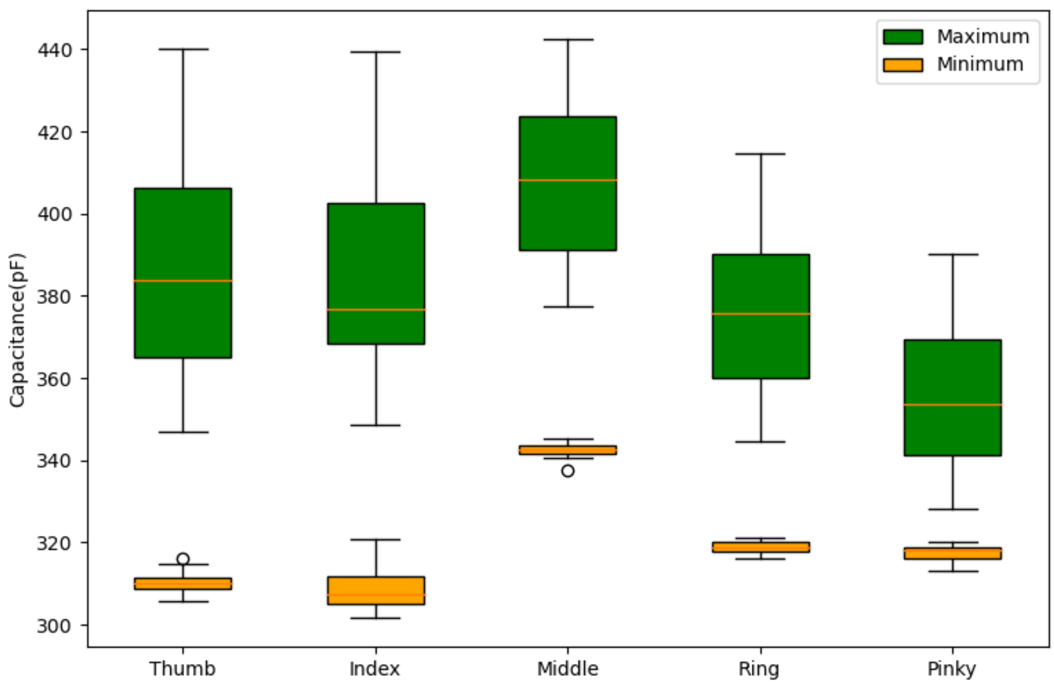
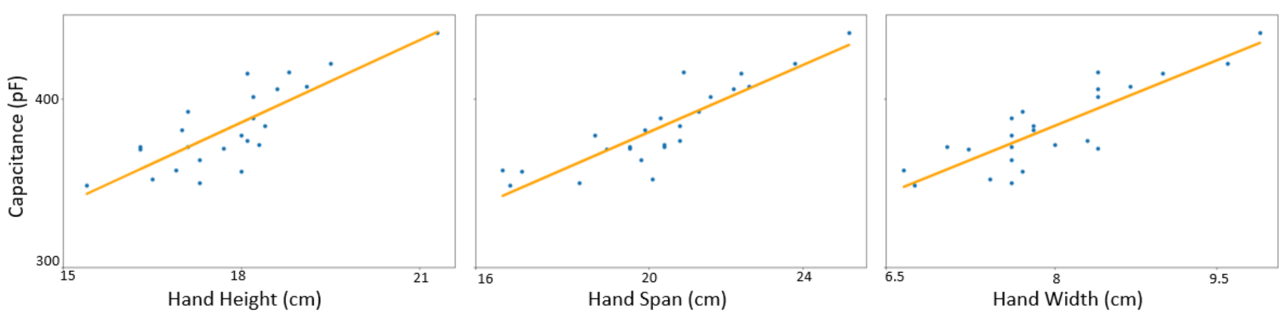


Figure 9. Maximum and minimum capacitance readings of all participants



(a) (b) (c)

Figure 10. Maximum capacitance correlation to (a) hand height, (b) hand height and (c) hand width for the index finger

This information provided us with a new insight on the readings of the sensors, which allowed us to minimize the capacitance variance observed in Figure 8 for the bent fingers. We decided to process the data, and map the capacitance values to a scale from 0 to 100. We then plotted these values in Figure 11. This plot shows that the variance in some cases has become smaller for the bent fingers. More complex data processing would then provide better data of the readings, which would then allow for gesture differentiation among all participants.

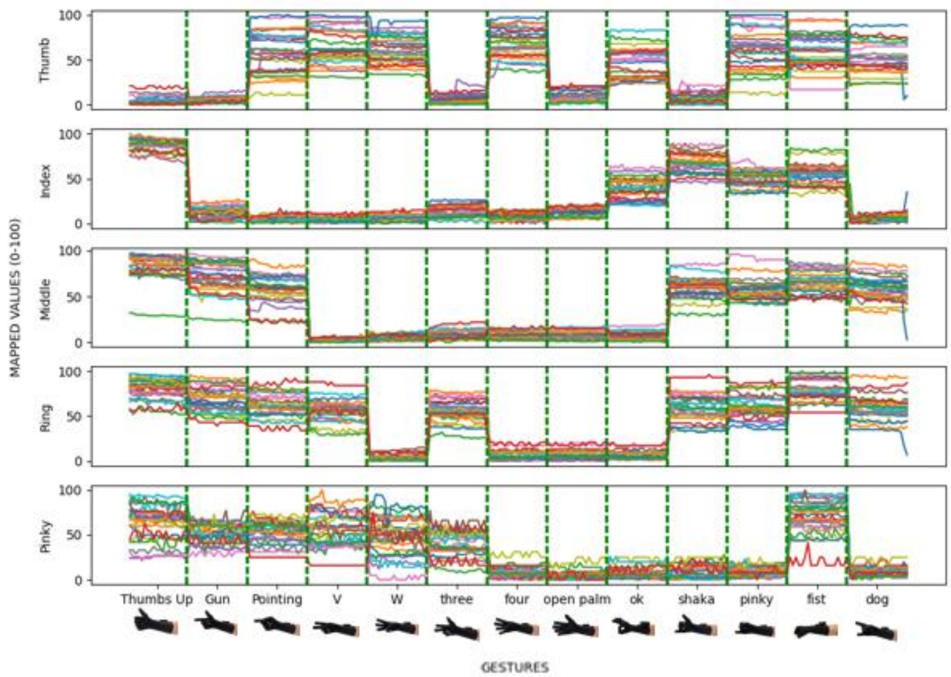


Figure 11. Mapped values of all participants vs the gestures being performed over time

5. CONCLUSIONS

The experiment presented in this paper shows results about the potential dielectric elastomer sensors have in hand gesture recognition. Hand static gestures can be differentiated, because the readings of the sensors vary with the bending of the fingers. The more a finger is bent, the higher the capacitance reading of the corresponding sensor. Although, the sensor readings vary from user to user, it was shown that there is a linear correlation between the sensor readings and the different hand sizes. The bigger the hand, the longer the stretch of the sensors and therefore, the higher the maximum capacitance readings. This correlation allows for data processing that can group the readings together for gesture recognition. These results bring us closer to the overall goal of this study, which is to development a hand gesture recognition glove for underwater communication.

Although it was not discussed in this paper, it is significant to mention that machine learning algorithms can be implemented to process the sensor readings and differentiate the gestures. It is also important to mention that dielectric elastomer sensors are not only promising in hand gesture recognition, but in all motion recognition. Sensors could be placed in different parts of the body to recognize different joint movements.

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