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MODELLING OF FLEX SENSOR RESISTANCE VALUE FOR FINGERSPELLING RECOGNITION PROTOTYPE USING SENSOR-BASED SIGNAL

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ABSTRACT: Individuals with hearing and speech impairments often rely on sign language to communicate with each other. While the hearing and speech impairment community can understand sign language to communicate with each other, individuals with normal hearing generally do not understand sign language. However, communication between the hearing and speech-impaired individual and a normally hearing individual can be made possible by fingerspelling with the help of a fingerspelling recognition system. Current research in fingerspelling recognition systems aims to improve the system's accuracy, rather than focusing on the ability of the system to convert the fingerspelling for real-time communication. The developed system can be computationally complex when the research aims to improve accuracy, resulting in unsuitability for real-time communication due to the extensive processing needed and oversized non-wearable hardware. Hence, this paper presents one of the options in developing a fingerspelling recognition system prototype that aims for ease in real-time communication using sensor-based signals. The prototype comprises a hand glove equipped with five flex sensors, designed to recognize and convert the hand gestures into the fingerspelled letters. Each flex sensor is fitted along the length of each finger to capture the gestured fingerspelling, measuring the changes in the flex sensor's resistance as it bends. The flex sensor resistance value was then modelled for fingerspelling recognition through demonstration on five users in the preliminary characterization, and later by ten users to obtain the system accuracy. An Arduino MEGA 2560 platform processed the sensor's data, which then transmits the recognized fingerspelled letters to an OLED display. The average recognition accuracy recorded for the prototype is 76.15% which is 15.38% higher than the preliminary characterization, indicating the possibility of using sensor-based signals in a fingerspelling recognition system for real-time communication. This system allows individuals with hearing and speech impairment to make various hand gestures while wearing the hand glove, which will be recognized as the corresponding fingerspelled letters for easy communication with individuals with normal hearing.

ABSTRAK: Individu dengan kekurangan pada pendengaran dan pertuturan biasanya bergantung kepada bahasa insyarat bagi berkomunikasi antara satu sama lain. Walaupun komuniti dengan kekurangan pada pendengaran dan pertuturan boleh memahami bahasa isyarat bagi berkomunikasi antara satu sama lain, individu dengan pendengaran normal secara amnya tidak memahami bahasa isyarat. Walau bagaimanapun, komunikasi antara individu kekurangan pada pendengaran dan pertuturan, dengan individu normal boleh diwujudkan melalui ejaan jari dengan bantuan sistem pengecaman ejaan jari. Kajian terkini dalam sistem pengecaman ejaan jari bertujuan bagi meningkatkan ketepatan sistem, bukan memfokuskan kepada kebolehan sistem dalam menterjemah ejaan secara masa nyata. Apabila tujuan kajian tersebut adalah bagi meningkatkan ketepatan, sistem yang terbina boleh menjadi sangat kompleks dalam pengiraannya, mengakibatkan sebuah sistem yang tidak sesuai bagi tujuan komunikasi masa nyata kerana memerlukan proses berlebihan dan perkakasan bersaiz besar yang tidak boleh dipakai. Oleh itu, kajian ini memberi pilihan dalam membangunkan sebuah prototaip sistem pengecaman ejaan jari, bertujuan memudahkan komunikasi masa nyata menggunakan isyarat berasaskan penderia. Prototaip ini terdiri daripada sebuah sarung tangan yang dilengkapi dengan lima penderia lentur, direka bagi mengenalpasti huruf yang dieja jari pada gaya tangan. Setiap penderia lentur dimuatkan sepanjang setiap jari bagi mengesan ejaan jari yang digayakan. Ukuran dibuat melalui perubahan rintangan penderia lentur apabila ianya dibengkokkan. Nilai rintangan penderia lentur ini kemudiannya dimodelkan bagi pengecaman ejaan jari melalui demonstrasi ke atas lima pengguna dalam perincian awal, dan seterusnya oleh sepuluh pengguna bagi mendapatkan ketepatan sistem. Data penderia tersebut diproses menggunakan platform Arduino MEGA 2560, dan huruf ejaan jari yang telah dikenal pasti dipaparkan ke paparan OLED. Purata ketepatan pengecaman yang direkodkan bagi prototaip ini adalah 76.15% di mana 15.38% lebih tinggi dari perincian awal, menunjukkan potensi penggunaan isyarat berasaskan penderia dalam sistem pengecaman ejaan jari bagi komunikasi masa nyata. Sistem ini membolehkan individu kekurangan pada pendengaran dan pertuturan membuat pelbagai gaya tangan sewaktu memakai sarung tangan ini, kemudian huruf ejaan jari yang sepadan akan dikenalpasti bagi memudahkan komunikasi bersama individu normal.

KEYWORDS: *Fingerspelling, Flex Sensor, Hand Gesture, Sign Language.*

1. INTRODUCTION

A forecast by the World Health Organization (WHO) stated that one in four people worldwide will have hearing impairment by 2050 [1]. Focusing on Malaysia, the Department of Social Welfare reported that about 46,127 individuals are currently affected by hearing impairment [2]. In general, interactions between individuals with hearing impairment and individuals with normal hearing have always been a troublesome task. This is because not everyone can comprehend sign language. Around the world, the use of sign language varies according to countries such as 'Bahasa Isyarat Malaysia' (BIM) in Malaysia [3], American Sign Language (ASL) in United States [4], Mexican Sign Language (LSM) in Mexico [4], and 'Bahasa Isyarat Indonesia' (BISINDO) in Indonesia [5]. Each sign language has its own uniqueness in either using both or one hand, but there are also some similarities in these sign language gestures, depending on their origin. Therefore, researchers in the area have been developing sign language recognition systems that are customized to the sign language in use, such as FingerSpeller [6], GestureSpeak [7], SpellRing [8], and SHWASI [9].

FingerSpeller recognized ASL fingerspelling using a wearable keyboard with several sensors embedded on rings [6]. The user must wear the ring on each finger, where hand gestures will be translated to text. While the average accuracy of the system can achieve up to 91%, each user had to personally collect their fingerspelled inputs to train the system for the customized recognition system. This requires additional procedures from the user to recheck their collected data to ensure accurate data was recorded as the training input. SpellRing also recognized ASL fingerspelling, but it utilized active acoustic sensing to detect hand gestures by a ring worn on the thumb, and a gyroscope [8]. The system can achieve up to 89.89% accuracy, but it needs a larger dataset in the recognition system's pre-trained model to be user-independent. Furthermore, the system needs to be physically connected to a personal computer for recognition processing, which can be bulky and impractical for real-time communication. On the other hand, SHWASI requires users to make specific hand gestures according to a pre-defined set of movements using a hand glove attached with flex sensors [9]. The system provides three modes for the recognition options to translate into phrases, letters, or alphabets other than letters. While the system's accuracy can be up to 79%, users had to learn a new set of pre-defined finger gestures to use the system. It can be challenging for users to learn pre-defined finger gestures just to use the system, as they are used to their daily standard sign language. GestureSpeak is an ASL fingerspelling recognition system developed to achieve a high recognition accuracy through a computationally efficient algorithm for faster response time [7]. The system requires data training using images of various hand gestures and can achieve up to 98.42% accuracy. While the accuracy is the highest compared to the other sensor-based systems mentioned, GestureSpeak is a vision-based system not yet deployed in hardware for real-time communication, as the reported result was based on an experimental setup [7]. Still, the system developed by researchers in the area proved that researchers are now moving towards improving the accuracy of the fingerspelling recognition system while aiming for the system to be utilized in real-time communication.

Hence, this paper explores one of the possibilities: developing a fingerspelling recognition system with acceptable accuracy that is enough to be used in real-time communication. This work aims to bridge the communication gap between hearing impaired individuals and normal hearing individuals using sensor-based signals in the fingerspelling recognition system. The proposed work in this paper incorporates flex sensors into a hand glove to capture finger movements as a sign language interpreter. It provides real-time output that displays the recognized letter. It is a promising initiative that can significantly enhance accessibility and communication for the hearing and speech-impaired community. The following section in this paper shares the background review in the area, while the following section explains the modelling and development of the fingerspelling recognition prototype. The following section presents the prototype demonstration and analysis of the system's accuracy in recognizing the letters. The last section concludes with the findings of this paper and future work that can be done in the area.

2. BACKGROUND STUDY

Sign language recognition systems can bridge the communication gap between sign language users and non-users by identifying and converting sign language into frequently spoken languages, allowing for seamless interaction and understanding [10]. They also play an important role in empowering the hearing-impaired community by giving them the ability to communicate more freely and effectively with a wider community. In addition, hearing impaired individuals can communicate through sign language more easily using fingerspelling.

2.1. Fingerspelling Recognition System

Fingerspelling involves representing the alphabet with one hand. It helps introduce new phrases and concepts, particularly when discussing words, names, or places without agreed-upon signs within the sign language community [11]. In fact, all words used by normal hearing individuals can be derived through fingerspelling. As such, the normal hearing community can also understand the messages conveyed by the hearing and speech impairment community without knowing the sign language beforehand, if there is a system that can translate the fingerspelling into text display. Such a system is also called a fingerspelling recognition system. In Malaysia, the fingerspelling practices by the hearing and speech impairment community follow the BIM as shown in Figure 1 [12]. The fingerspelling in BIM is gestured by using one hand for all letters, with exceptions for letters ‘J’ and ‘Z’ that are accompanied by some specific hand movement.

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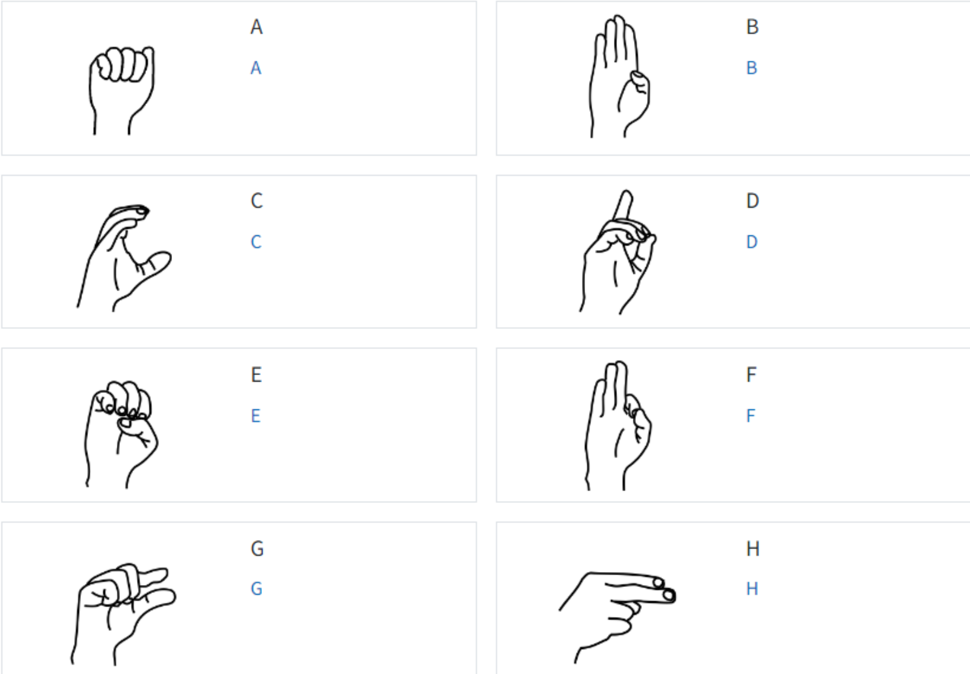

Figure 1. Sign language gestures for some of the letters in 'Bahasa Isyarat Malaysia' (BIM) [12].

A fingerspelling recognition system can either be developed by a vision-based or sensor-based system [13]. While a vision-based system uses images to convert the fingerspelling gesture into text, a sensor-based system uses readings obtained from sensors to convert the fingerspelling gesture [14]. As such, vision-based systems usually require a high-performance computing platform for image processing that uses high-end hardware and software in their developmental phase. This is because a vision-based system is sensitive to factors affecting the image properties, such as surrounding illumination, image resolution, and colour variation, to achieve a high-accuracy system [5]. This resulted in an impractical system more suitable for the research and developmental phase than for real-time communication. In domestic use for real-time communication, a sensor-based system is an appropriate alternative as it can utilize the off-the-shelf (OTS) components that are wearable. Although it is wearable, a sensor-based system can help translate fingerspelled gestures with accuracy that is enough for real-time fingerspelling recognition [6][8][9]. The following section will further explain insights into the sensor-based approach for the fingerspelling recognition system.

2.2. Sensor-based Fingerspelling Recognition System

In a broader sense, sensor-based sign language recognition systems use sensors to capture and interpret the gestures and movements made during sign language communication [15]. Such a system relies on sensor data, such as flex sensors, accelerometers, or wearable devices, to detect and analyze the hand and arm movements involved in sign language gestures. By processing the sensor data, sensor-based systems can recognize and translate signs and gestures into text or speech, facilitating communication for individuals with hearing and speaking impairments. An example of a sensor-based sign language interpreter system is shown in Figure 2.

The system in Figure 2 uses flex sensors attached to the fingers to detect the bending of the fingers when the user is gesturing the sign language. The inertial measurement unit (MPU 6050) is also used to measure the dynamic and static gestures of the hand from the gyroscope and accelerometer readings. The data obtained from the flex sensors and the inertial measurement unit are processed by the Raspberry Pi as the processor platform [16]. Once the sign language gestures had been translated and identified, the Raspberry Pi sends the data for display through the LCD and is voiced out by the speaker.

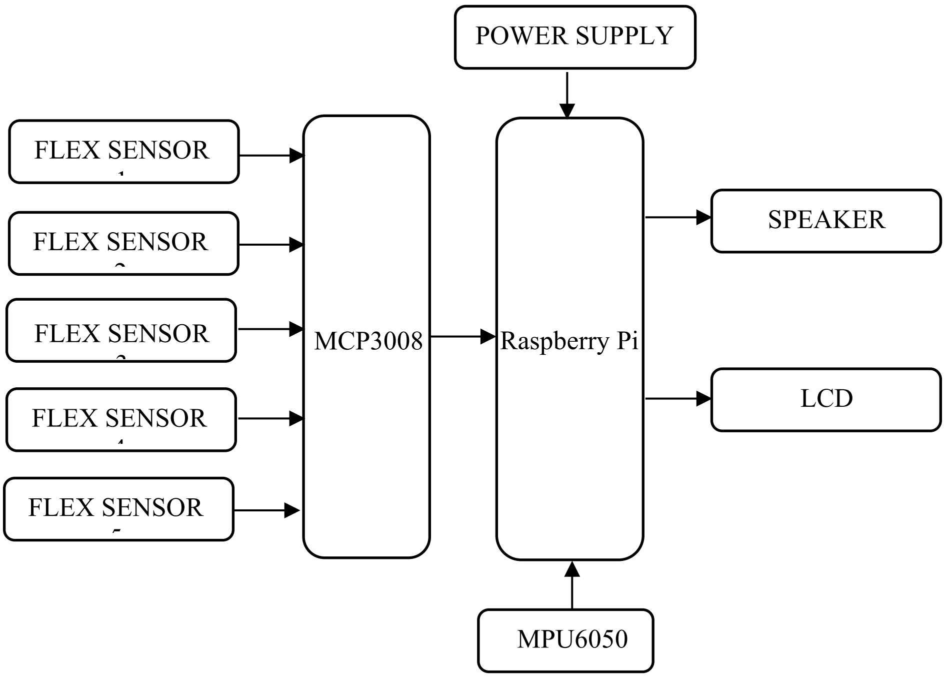

Figure 2. Sensor-based sign language interpreter system [16].

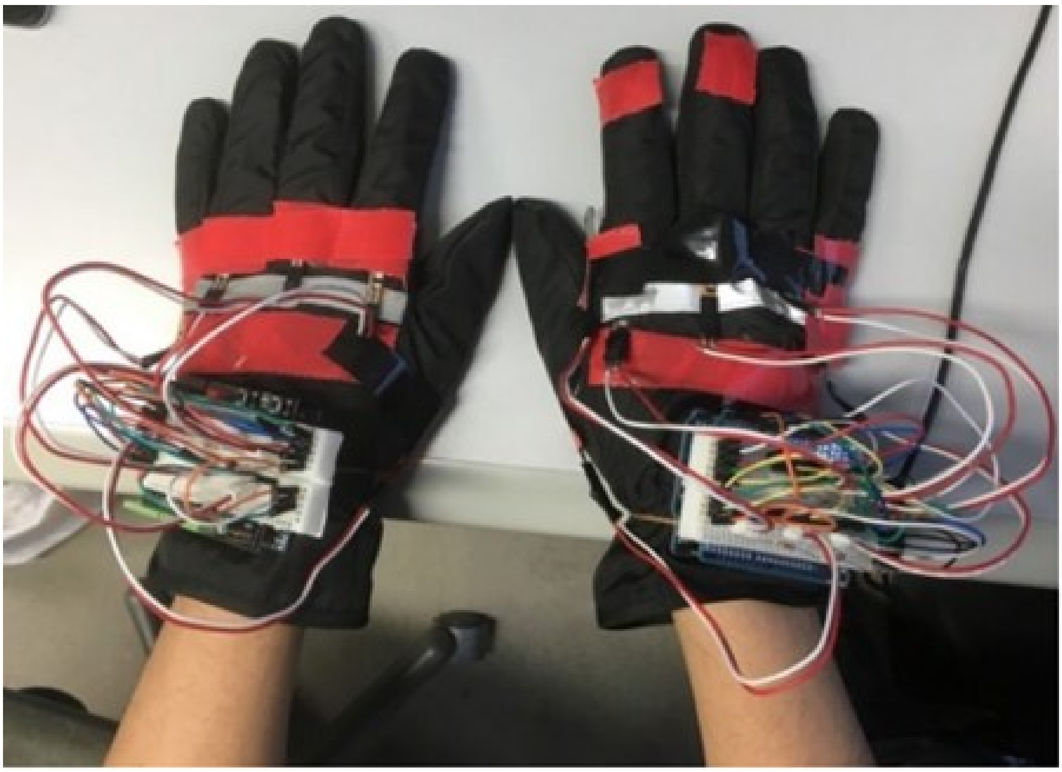

Figure 3. Prototype of sensor-based sign language interpreter glove system using accelerometer [17].

Two commonly used sensors in sensor-based sign language recognition systems are flex sensors and accelerometers. A flex sensor is used to detect finger bending (usually attached to a glove) as the resistance of the sensor changes when the finger is bent, allowing the system to capture the changes in movements involved in sign language [15]. On the other hand, the accelerometer helps detect dynamic gestures like the alphabet's J' and 'Z' in BIM and ASL. These alphabets involve hand movements that are not easily captured by static sensors like flex sensors. The accelerometer, which measures the acceleration of the hand or fingers, helps to detect the dynamic movements involved in these two alphabets. Figure 3 shows an example of a sign language recognition system prototype using the accelerometer [17]. The accelerometer in Figure 3 was used to detect the hand motion in translating sign language.

3. MODELLING AND DEVELOPMENT OF FINGERSPELLING RECOGNITION PROTOTYPE

Based on the background study in the previous section, the prototype of the fingerspelling recognition system in this paper was developed as shown in Figure 4, the block diagram. Five flex sensors were connected to the Arduino MEGA 2560 platform as the input that sensed each finger's bending signal. These flex sensors were fixed on the hand glove that the user needs to wear. An accelerometer was added as a sensor to detect the movement of the letters 'J' and 'Z'. The output of the prototype includes green and red LEDs, a buzzer, and an OLED display. The green and red LEDs served as indicators for valid or invalid sensor readings, while the buzzer would be triggered once a letter had been recognized from the valid sensor reading. The OLED display would show the letters detected from the sensor readings and the analog-to-digital (ADC) readings detected from the flex sensors.

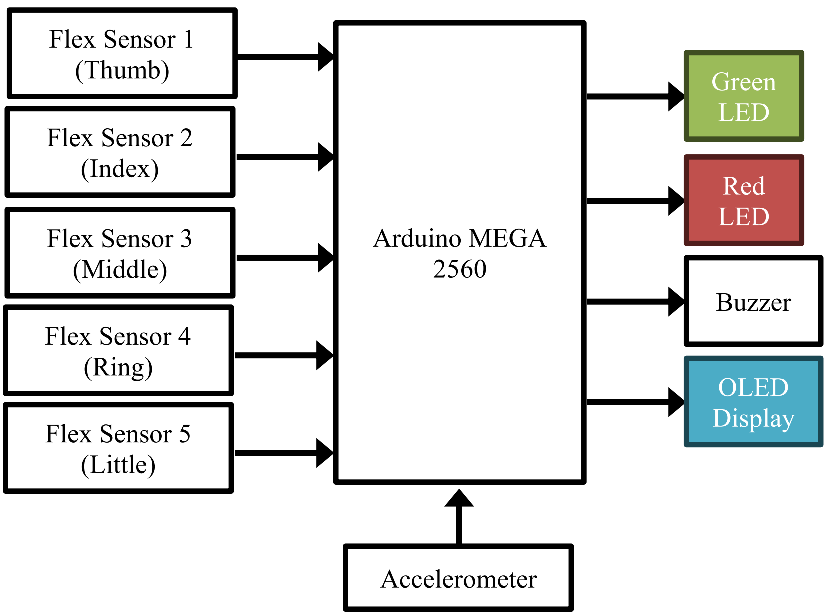

Figure 4. Block diagram of the developed fingerspelling recognition prototype.

The schematic diagram of the prototype is shown in Figure 5. The two LEDs and buzzer are connected to the digital pins (D8, D9 and D13) of the Arduino MEGA 2560, while the five flex sensors can be seen connected to the analog pins of the board (A0, A1, A2, A3 and A4). Each component was accompanied by suitable resistors to limit the current flow through the pins. The OLED display and accelerometer both use the I2C pins on the Arduino MEGA 2560, where the access time between the two components was controlled through the program code to enable valid communication between the two components. The printed circuit board (PCB) configured for the prototype is divided into two boards, where one PCB is for the Arduino MEGA 2560 and its peripherals, other than the accelerometer, while the other PCB is for an isolated accelerometer.

The PCB developed for the Arduino MEGA 2560 connections is shown in Figure 6. The top view in Figure 6 shows the green and red LEDs, buzzer, OLED display, and headers for flex sensor connections. There are also headers for future system expansion on the PCB, as labeled in Figure 6. The bottom view in Figure 6 shows the circuit route between the inputs and outputs to the Arduino MEGA 2560 pins. The input and output components of the prototype were connected to the PCB board via male or female connectors, respectively. The PCB's corresponding top and bottom views were also labeled in Figure 6 to show the relationship between both views concerning their headers and pins.

The other PCB that housed the accelerometer can be seen in Figure 7. The accelerometer was connected to an isolated PCB because it needs to be attached to the hand glove for hand movement detection. As the accelerometer shared the I2C pins with the OLED display in its connection to the Arduino MEGA 2560, the programming code controls access to the I2C serial communication. The isolated PCB for the accelerometer in Figure 7 can be seen in Figure 8, attached to the hand glove. This is because hand movement can be precisely sensed if the accelerometer is placed on top of the user's hand, rather than housed on the same PCB as the Arduino MEGA 2560 platform.

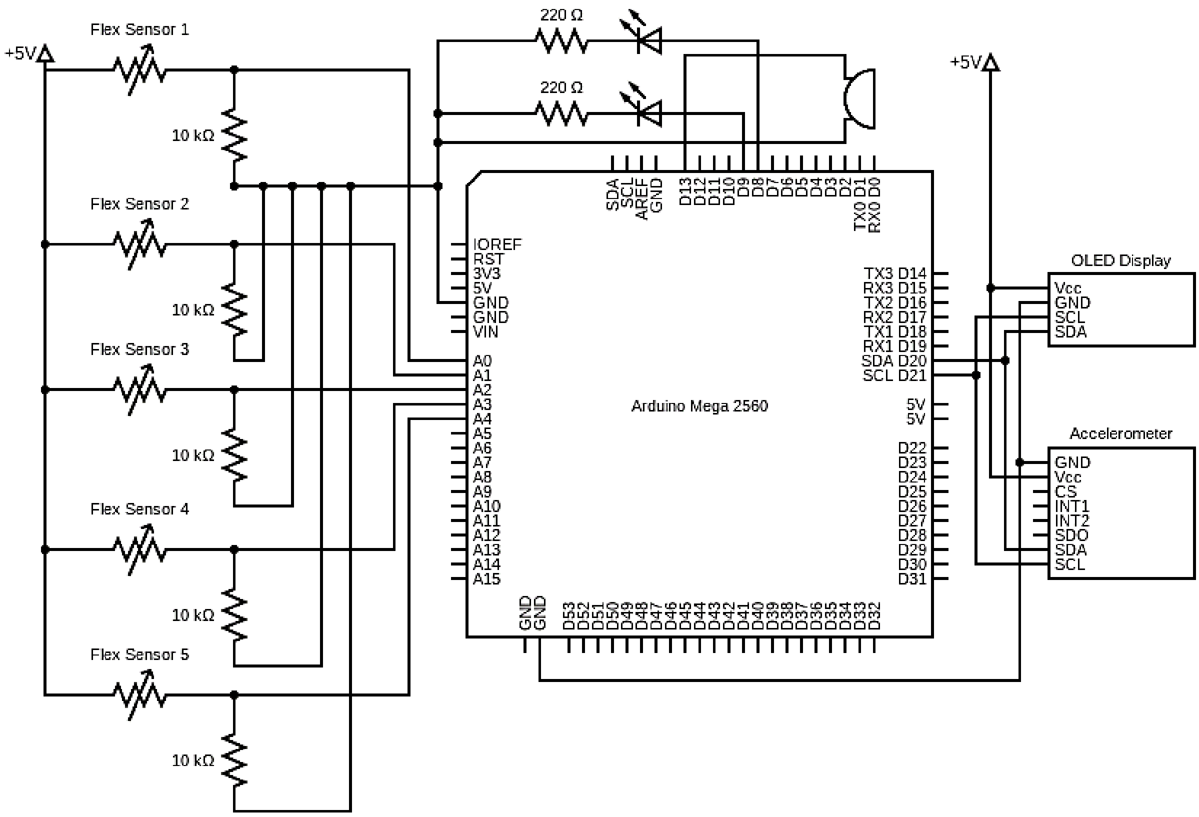

Figure 5. Schematic diagram of the fingerspelling recognition prototype.

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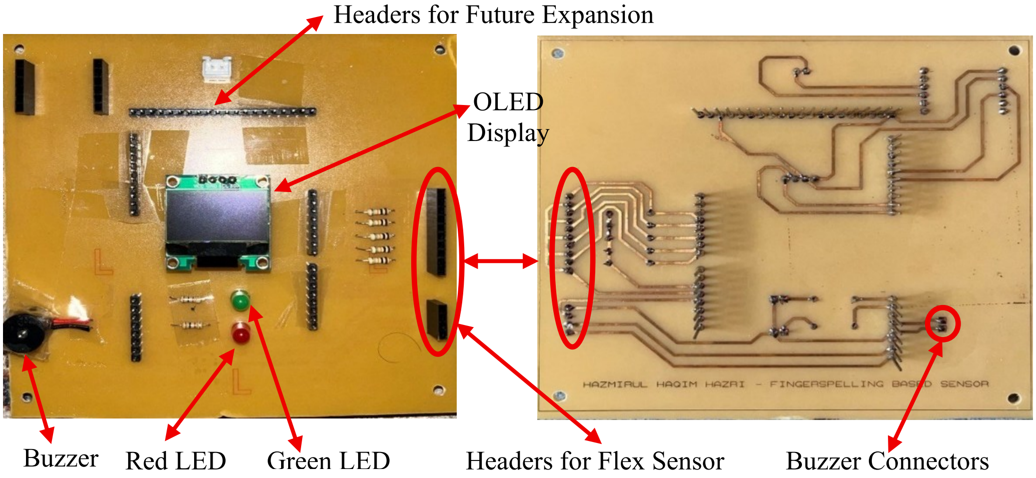
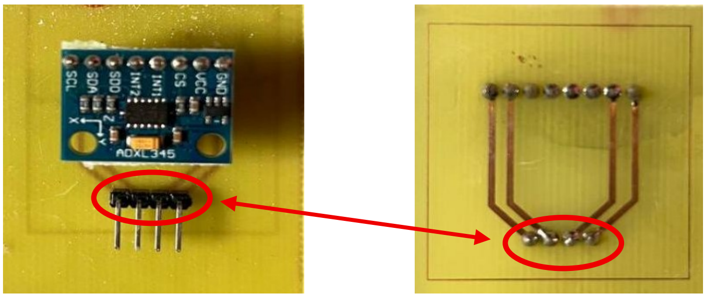


(a) Top view (b) Bottom view

Figure 6. Top and bottom views of the prototype's PCB, with labels showing the corresponding pins on both views.



(a) Top view (b) Bottom view

Figure 7. Top and bottom views of the accelerometer's isolated PCB, with labelling to show the top and bottom view connections.

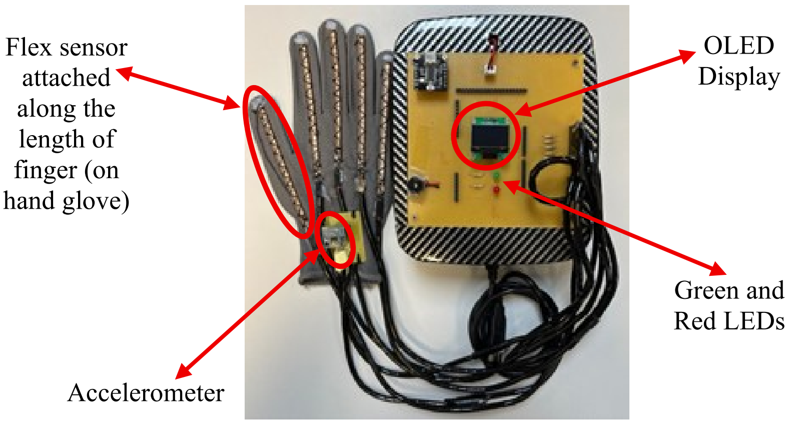


Figure 8. Final prototype of the developed fingerspelling recognition system.

Figure 8 shows the final prototype of the developed fingerspelling recognition that combines both PCBs, as shown in Figs. 6 and 7. The hand glove in Figure 8 was attached with the flex sensors along the length of each finger, together with the isolated PCB that housed the accelerometer. Once a hearing impairment user wears the hand glove and gestures a fingerspelling, the flex sensors will sense the resistance value produced by the finger's bending, where the readings are converted to their ADC values by the Arduino MEGA 2560. Through the fingerspelling recognition processing in the Arduino MEGA 2560 program code, the OLED display in Figure 8 will display the recognized letter for a normal hearing individual to understand the fingerspelling. In Figure 8, the Arduino MEGA 2560 was housed in the enclosed box. A power bank will power the prototype to ease its mobility and enable its portability. Figure 9 shows the steps involved in modeling the flex sensor's resistance value for the prototype, which consists of two main processes: preliminary characterization and improved characterization.

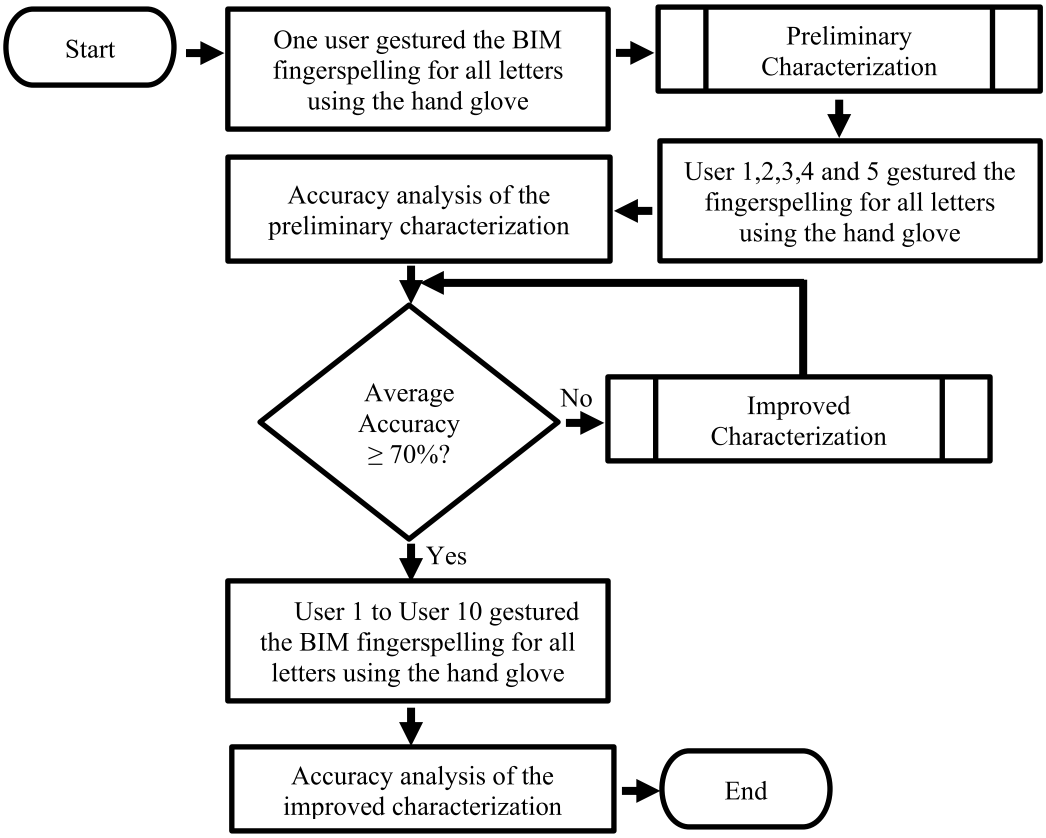


Figure 9. Steps involved in the prototype’s modeling of flex sensors' resistance value.

In the preliminary characterization process shown in Figure 9, the flex sensors' resistance produced by one user when the BIM fingerspelled each letter was gestured is recorded in its converted ADC value. The converted ADC values from this user act as the threshold values for each BIM fingerspelled letter in the preliminary characterization. The threshold values were used in a conventional if-else algorithm for the fingerspelling recognition processing to map the hand gestures to the fingerspelled letters. The threshold values in the preliminary characterization for the fingerspelling recognition processing are shown in Table 1. Afterwards, the prototype was tested by five users, and their flex sensors' resistance values were recorded to determine the accuracy of the prototype in the preliminary characterization. In this phase, the threshold values in the conventional if-else algorithm of the fingerspelling recognition processing were based on the threshold values given in Table 1.

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Table 1. ADC threshold values for the preliminary characterization in the fingerspelling recognition processing

	ADC Threshold Value for Each Flex Sensor based on Finger				
Letters	**Thumb**	**Index**	**Middle**	**Ring**	**Little**
A	433	253	272	283	224
B	316	486	511	501	446
C	369	386	379	420	427
D	343	469	305	336	276
E	289	261	277	308	249
F	286	290	476	494	440
G	432	418	254	268	199
H	322	476	479	304	268
I	288	246	280	336	423
J	367	306	333	367	446
K	331	481	502	342	277
L	431	468	281	293	248
M	296	264	316	306	228
N	364	270	282	291	221
O	343	344	337	380	387
P	397	480	482	431	202
Q	456	443	299	311	247
R	355	477	501	341	295
S	331	279	330	370	268
T	399	274	305	313	267
U	356	481	512	354	309
V	350	483	509	383	333
W	336	491	507	501	298
X	334	444	289	307	261
Y	342	333	372	394	448
Z	376	488	321	363	296

Based on the accuracy analysis of the five users in the preliminary characterization, the threshold values of the fingerspelling recognition processing were enhanced in the improved characterization process if the average recognition accuracy was less than 70%. The average recognition accuracy value of 70% was chosen as a proof-of-concept for this prototype's potential as a fingerspelling recognition system. In the improved characterization process, the threshold values of the fingerspelling recognition processing were enhanced based on the recorded flex sensors' ADC values of the five users in the preliminary characterization for each letter. The improvement was made by focusing on the letters that achieved an average accuracy of less than 70%, where the threshold values were increased according to the highest recorded ADC values of the five users. The new threshold values (meaning the highest recorded ADC values concerning letters that achieved less than 70% average accuracy) will be utilized in the conventional if-else algorithm of the fingerspelling recognition processing in the improved characterization process.

At this time, the same five users will test the prototype repeatedly until the average accuracy of the system is 70% or higher. This is because, every time changes were made to the threshold values in the conventional if-else algorithm of the fingerspelling recognition processing, the average accuracy according to each letter recognition also changed. In turn, it is not guaranteed that once the threshold values of the focused letters are changed, the accuracy of the letters where the threshold values remain unchanged will stay the same. As a result, the prototype had to be tested repeatedly in the improved characterization process to get the best threshold values that can compromise the prototype's potential in recognizing the fingerspelled letters, such that its average accuracy achieved 70% at most.

Once the prototype's average accuracy hit 70% or higher, the utilized threshold values were fixed in the conventional if-else algorithm of the fingerspelling recognition processing. The latest fixed threshold values in the improved characterization for the fingerspelling recognition processing are shown in Table 2. By utilizing the threshold values in Table 2, the prototype was then tested by ten users to get its final average accuracy. The final average accuracy will then be analyzed for each letter's recognition to conclude the developed prototype's potential as a fingerspelling recognition system that utilizes the sensor-based signal.

Table 2. ADC threshold values for the fingerspelling recognition processing following the improved characterization process, once the prototype accuracy is higher than 70%

	ADC Threshold Value of Each Flex Sensor based on Finger				
Letters	**Thumb**	**Index**	**Middle**	**Ring**	**Little**
A	403	250	254	287	209
B	320	479	482	488	443
C	387	351	346	357	377
D	341	467	311	279	260
E	314	271	283	300	243
F	340	281	478	486	439
G	411	390	245	257	206
H	373	474	477	315	252
I	323	299	300	327	437
J	320	315	317	340	438
K	361	477	472	282	236
L	448	452	252	278	224
M	328	261	282	284	223
N	364	252	271	241	216
O	323	308	316	307	293
P	368	439	361	307	227
Q	427	439	254	290	213
R	328	468	466	234	242
S	290	275	274	277	209
T	374	288	249	270	208
U	319	425	479	282	289
V	318	422	485	324	285
W	330	418	483	479	270
X	318	300	256	258	212
Y	441	368	304	337	438
Z	322	384	271	275	216

4. RESULT AND ANALYSIS

Table 3 demonstrates the prototype's inputs and outputs when a user is gesturing five letters: 'A', 'B', 'C', 'D', and 'E'. The letters were gestured using the BIM fingerspelling, where the resistance value of the flex sensors on the hand glove was recorded as the prototype's input. These inputs, which were translated into their ADC values, are processed by the conventional if-else algorithm in the fingerspelling recognition processing to recognize the fingerspelled letters. The prototype then displays the recognized letter on the OLED display for real-time communication, as shown in Table 3.

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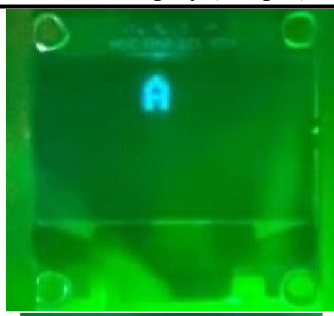
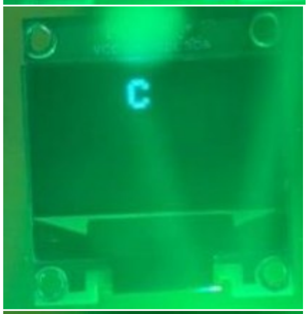
Table 3. Demonstration of the prototype operation when a user was using BIM fingerspelling for the letters 'A' to 'E'

Letter	Hand Gesture (Input)	OLED Display (Output)
A		
B		
C		
D		
E		

The average recognition accuracy of the prototype in the preliminary characterization for five users is given in Figure 10, where each user was labeled as *User 1*, *User 2*, *User 3*, *User 4,* and *User 5*. It can be seen in Figure 10 that the highest average accuracy is up to 88.46%, which was recorded for User 3, while the lowest average accuracy is 42.31% for *User 2*. The difference in average accuracy for each user is due to the variation in the length of each user's fingers. When the length of fingers differed for each user, the flex sensors would record different resistance values when bent, depending on the placement and fit of the hand glove on the user's hand. Hence, the choice of threshold values in the fingerspelling recognition processing plays a vital role in increasing or decreasing the average recognition accuracy of the prototype.

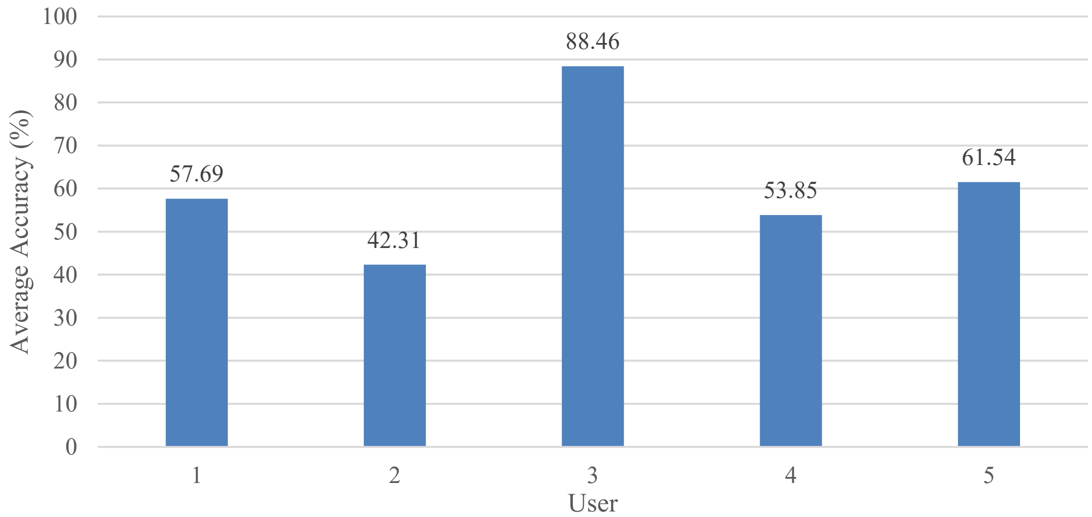


Figure 10. Average accuracy of the fingerspelling recognition system for five users using preliminary characterization values.

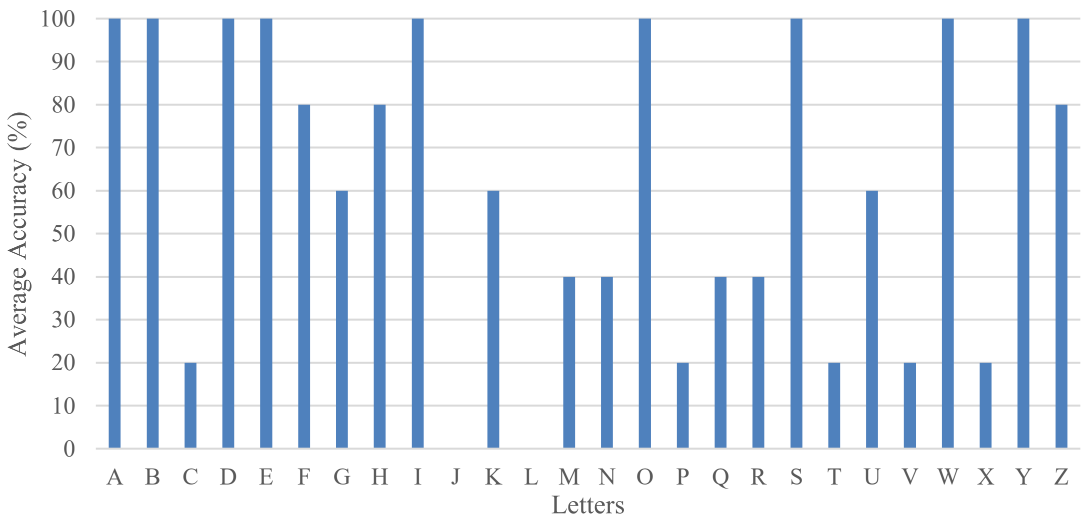


Figure 11. Average accuracy of the fingerspelling recognition system for each letter recognition using preliminary characterization values.

Figure 11 shows the average accuracy of the prototype in recognizing each letter for five users in the preliminary characterization. The average recognition accuracy of each letter shown in Figure 11 ranges from 0% to 100%. For letters such as 'A', 'B', 'D', 'E', 'I', 'O', 'S', 'W', and 'Y', the average recognition accuracy is 100%. The lowest average accuracy of 0% was recorded for letters 'J' and 'L', indicating that the prototype cannot recognize these two letters in the preliminary characterization. The average recognition accuracy for the rest of the letters varied between 20% to 80%. Based on the average accuracy in Figure 11, the total average accuracy of the fingerspelling recognition system in the preliminary characterization is 60.77%. The average accuracy of 60.77% is lower than the target of 70% for the system accuracy, which was later improved in the improved characterization process that follows.

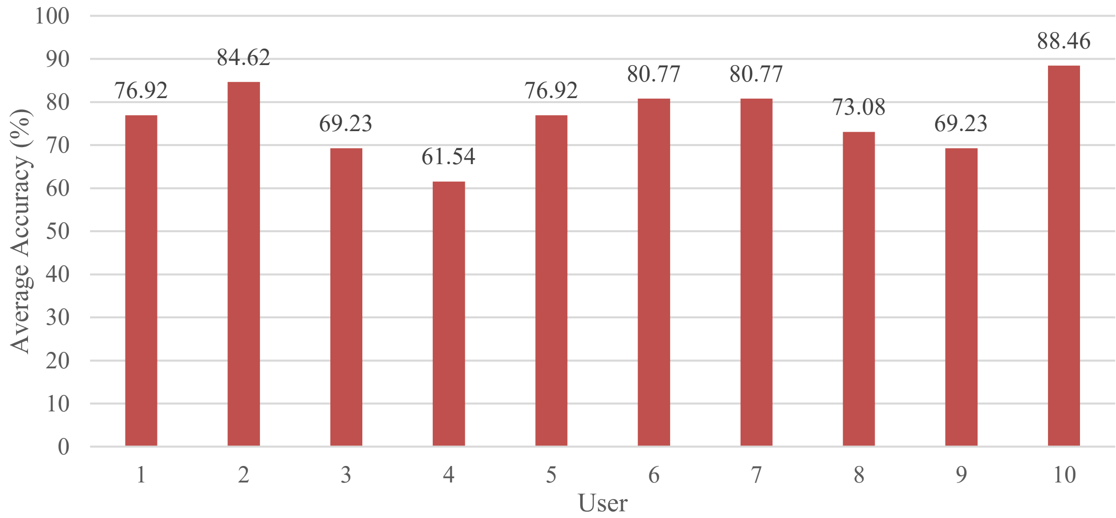


Figure 12. Average accuracy of the fingerspelling recognition system using improved characterization values for ten users.

Once the total average accuracy reached 70% in the improved characterization for the five users tested earlier, the prototype was tested by ten users using the latest fixed threshold values in the improved characterization. The average recognition accuracy of the improved characterization for ten users and all letters is shown in Figs. 12 and 13. It can be observed in Figure 12 that the average recognition accuracy for each user is above 60% in the improved characterization. The highest average recognition accuracy is 88.46% for *User 10,* while the lowest average recognition accuracy is 61.54% for *User 4*. Compared to the preliminary characterization, the prototype shows a significant increment of 19.23% in the lowest user's average recognition accuracy in the improved characterization.

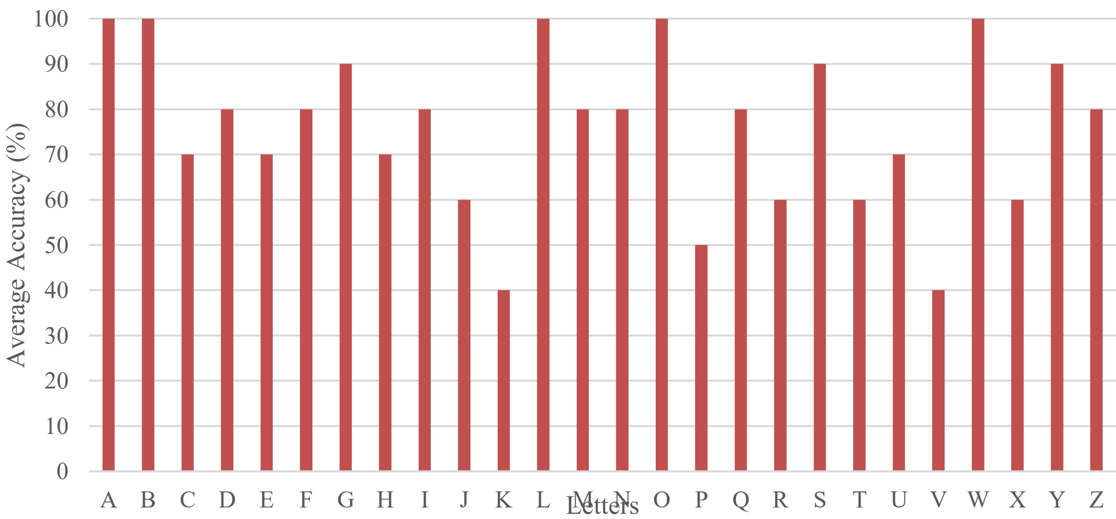


Figure 13. Average accuracy of the fingerspelling recognition system using improved characterization values for each letter detection.

The average recognition accuracy for all letters using the improved characterization values also recorded significant increment in the lowest average recognition accuracy, which is 40% for the letters ‘K’ and ‘V’ as shown in Figure 13. This is because both letters share the same gesture in BIM fingerspelling for index and middle fingers, with slight gesture needed from the thumb for gesturing the letter ‘K’. The threshold values in the improved characterization may have mixed up the recognition of these two letters based on the flex sensors' reading, resulting in low average recognition accuracy. Still, only five letters achieved an average recognition accuracy of 100% in the improved characterization, for the letters ‘A’, ‘B’, ‘L’, ‘O ’, and ‘W’, compared to nine letters in the preliminary characterization. This makes up for the unrecognized letters in the preliminary characterization, ‘J’ and ‘L’, which achieved 60% and 100% average recognition accuracy in each improved characterization. Overall, the total average accuracy for the prototype using the threshold values fixed in the improved characterization process is 76.15%, 15.38% higher than the total average recognition accuracy achieved in the preliminary characterization.

Table 4. Comparison of the proposed work with other reported works

Developed System	System Input	Recognition Processing	Sign Language	System Accuracy	Advantage / Limitation
FingerSpeller [6]	Accelerometers (embedded on five rings) / sensor-based	Hidden Markov Model (HMM) / machine learning	ASL	91.00 %	Promising initiative for real-time communication but requires users to perform data collection for personalized system training.
SpellRing [8]	Microphone and speaker (embedded on a single ring) / sensor-based	Connectionist Temporal Classification (CTC) / machine learning	ASL	89.89 %	Good recognition accuracy but requires the use of a personal computer for recognition processing, which is impractical for real-time applications (bulky hardware).
SHWASI [9]	Flex sensors (attached to a hand glove) / sensor-based	Low-level processing by Arduino UNO	Pre-defined Sign Language	79.00 %	This is a promising approach for real-time communication, but it requires users to learn a new set of predefined finger gestures to use the system, which can be troublesome for some users.
GestureSpeak [7]	Images / vision-based	EfficientNetV2-M and MobileNetV3-L/ deep learning	ASL	98.42 %	High recognition accuracy, but not yet deployed to an embedded hardware platform for real-time communication and use.
Proposed Work	Flex sensors (attached to a hand glove) / sensor-based	Conventional if-else algorithm by Arduino MEGA 2560	BIM	76.15 %	Ready to be used in real-time communication with promising recognition accuracy.

The average recognition accuracy of 76.15% shows that the prototype presented in this paper has the potential to be further refined for improvement as a real-time fingerspelling recognition system. Although the average recognition accuracy is the lowest compared to the other sensor-based systems mentioned, such as FingerSpeller (91%), SpellRing (89.89%), and SHWASI (79%), none of the mentioned systems utilize BIM fingerspelling. Besides, the mentioned systems mostly needed extra effort from the user for input training, either to enlarge the training datasets (FingerSpeller and SpellRing) or to get familiar with the pre-defined set of finger gestures customized for the system (SHWASI). This reduces the system's flexibility in being directly used in real-time communication. Still, the constant effort in the development approach for all the mentioned systems shows that researchers are concerned about the system's enhancement and the possibility of further benefiting the hearing and speech impairment community.

Table 4 compares the proposed work in this paper with the other promising fingerspelling recognition systems that other researchers have reported. It can be observed that while all developed systems are in the experimental and development phase, the proposed work in this paper is the closest initiative that can be utilized in real-time communication for a BIM fingerspelling recognition system.

5. CONCLUSION

This paper shares the flex sensor resistance value modeling for a fingerspelling recognition system using two main processes: preliminary characterization and improved characterization. The flex sensor resistance value was converted into its corresponding ADC readings, which were utilized for the threshold values in the initial characterization and improved characterization processes. In the preliminary characterization, user threshold values recorded for each flex sensor's resistance values produced for all fingerspelled letters were used in the fingerspelling recognition processing. The total average recognition accuracy when five users tested the system in this preliminary characterization process was 60.77%, which is lower than the average accuracy intended as the proof-of-concept of this prototype, which is 70%. The prototype was constructed using flex sensors and an accelerometer as inputs, Arduino MEGA 2560 as processing platform, and LEDs, buzzer, and OLED display as outputs.

In the improved characterization process, flex sensors' resistance values recorded earlier from the five users were analyzed to adjust the threshold values in the fingerspelling recognition processing. The fingerspelling recognition processing used the conventional if-else algorithm to map the hand gestures into their fingerspelled letters via the threshold values configured. The five users tested the prototype repeatedly using the improved threshold values until it achieved at least 70% recognition accuracy. Once the average recognition accuracy reached the target of 70%, the latest threshold values were fixed in the fingerspelling recognition processing algorithm. The total average accuracy of the system using the latest improved characterization threshold value is 76.15%, which is 6.15% higher than the targeted 70% value.

Still, there is room for improvement in this work, as the accuracy of 76.15% achieved is 23.85% less than the perfect accuracy of 100%. This might be due to the hand glove of this prototype, which is standard to one size and affected the system's accuracy, given the various sizes of users' hands during the demonstration. As the flex sensor was fitted at the same position along the length of the fingers on the hand glove, the bending of the flex sensors for different hand sizes imposed different resistance values due to the flex sensor's placement. The hand glove may fit nicely for one user but may be too loose for another due to different hand sizes. As such, the threshold values fixed for the system might work perfectly for one user during the fingerspelling recognition system, but not for the following user due to variation in the sensor's placement, which had already been fitted along the length of the fingers on the same hand glove. Future work in this direction can focus on a customized hand glove to be used for different hand sizes, which can be grouped into either male or female users.

Other potential future work includes consideration for an adjustable flex sensor placement on the hand glove, instead of preparing several separate hand gloves for individual sizes. The critical thing in this adjustable placement is to ensure that the flex sensor is fixed at the knuckles or joints of the fingers, where the bend of the fingers can be accurately measured. In this adjustment, the system can utilize the two available off-the-shelf (OTS) flex sensors, lengths that are either 2.2 inches or 4.5 inches, instead of only 4.5-inch flex sensors as utilized in this proposed work.

Furthermore, the prototype developed in this paper was tested by normal hearing individuals who are not frequent sign language users. This is another limitation of this work, where future work will include prototype demonstrations by users with hearing and speech impairments who are frequent sign language users. Suppose frequent fingerspelling users tested the prototype. In that case, the recognition accuracy achieved by the system is more focused on the targeted group of users, and the improvements made will directly cater to the needs of these users.

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