A Sign Language Recognition System Using Ionic Liquid Strain Sensor

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***Abstract*—In this report, we develop a system converting sign language into voices and text. The system includes a glove attached self-developed ionic liquid-based strain sensors on each finger to detect the movement of them. When the hand move to express a letter lead to the resistance of the strain sensors on each finger change. Therefore, through the information from a set of sensors, the system can recognize the letter that user want to convey. A measuring and data acquisition circuit also are developed to receive and analyze data from the sensors. Furthermore, a data digitizing method is proposed as a solution for decoding purpose. The system is tested with 10 distinguished basic letters in American Sign Language table (ASL). The results show the accuracy of system is 98%. The system operates stably with the low power of 0.81W at rest state and 1.71W when working. Besides, applications on smartphone and PC are also built to translate the data into text and speech. These apps make it easier to communicate with deaf people. With achieved results, the system is fully extensible to detect more letters in ALS table in the future.**

Keywords—sign language recognition, American Sign Language, strain sensor

I. INTRODUCTION

Deaf people who are unable to speak or hear do not use usual language to communicate with each other. According to World Health Organization, there are approximately 278 million deaf people in 2005 [1]. The number of those people increased by 82 million people in 2015 [2]. There are communication barriers between hearing people and deaf individuals either because signers may not be able to speak and hear or because hearing individuals may not be able to sign. This communication gap can cause a negative impact on lives and relationships of deaf people. A sign language is a useful method to enable communication and convey meaning. Around 300 sign languages are in use all over world today. Among them, American Sign Language (ASL) is one of the most popular sign language in the world. It is easy for deaf people to convey meaning as using sign language. Ordinary people, however, will not understand these languages if they do not learn about it. So, it is necessary to have a system that recognize and convert sign language into voice or letter. Thus, a low-cost, more efficient way of enabling communication between hearing people and deaf people is needed.

There are three popular methods for hand gesture recognition, including vision based, Electromyography (EMG) based and glove based. In vision based method, a camera is setup to capture the gestures of hand. The achieved image is then processed using different algorithms [3]–[8]. This approach has some limitations due to the use of 2D camera while the movements are in 3D. Furthermore, the system setup is complex and require a large place, an expensive processor.

In EMG based approach, EMG sensors are used to sense the muscle activity. These sensors extract multiple EMG signals, called electromyograms, from hand and wrist prostheses. Conductive electrodes are attached to the skin surface for detecting the movement of the hand [1], [9]–[13]. This is a novel technique, but it has the drawback that the signals are very weak, and vary significantly under different conditions. Consequently, these signals are very difficult to classify.

In terms of glove-based approach, this approach is conducted by attaching different sensors on hand glove to sense the bending, orientation and position of hand, and contact and spacing between fingers [14]. Different types of sensor are used on the glove that includes flexible tubes with light, capacitive electrode, flex sensors and magnetic sensors to detect the curl of finger. Accelerometer, Gyroscope and other tilt sensors are used for the orientation and position of hand, and proximity and touch sensors for the detection of contacts [15]–[18].

In this work, we developed a low-cost sign language recognition system using ionic liquid strain sensor, a type of wide range strain gauge that is interested in recent years [19]–[23]. The system include some strain sensors attached on the fingers. These sensors will sense the movement of each finger, the data from them is processed and decoded into voice or text by a processing circuit. Opposite people can understand the letter that user want to convey by hearing the voice from the speaker or watching the letter on the screen of the smartphone or PC.

II. MATERIALS AND METHODS

A. System

In this paper, a self-developed ionic liquid based strain sensors [20] are used for gathering information from a glove to identify the related position of the fingers for sign language recognition. Block diagram of the sign language recognition system using ionic liquid-based sensors is illustrated in Fig. 1. We use the four-point resistivity measuring technique to determine the resistance of sensor using ionic liquid through Howland current source and Wien bridge oscillator circuit. Wien bridge oscillator circuit generates a sinusoidal signal with a specified frequency to apply to the sensor. Howland current source holds the signal current stable through the sensor. Following this, the figure for each sensor is read in turn by a multiplexer. The hardware system is reduced significantly resources thanks to this multiplexer. The signal is then passed through a band-pass filter to eliminate noise. There are some noise that affect to the system include the low frequency noise (50, 60 Hz) from civil electrical system and the high frequency noise from environment due to hand or body movement. Next, the amplitude of the signal is separated by a peak detector before being sent to a microcontroller. In this study, we use Arduino KIT Pro mini as a central processor of the system. This KIT is popular, low cost, small size, so it is very suitable to the system. In the central processing block, the data is processed and decoded according to a programed algorithm before being displayed on the screen and played voice.

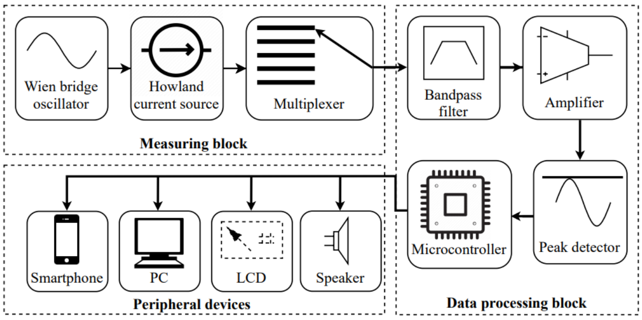


Fig. 1. Block diagram of the ionic liquid-based sign language recognition system

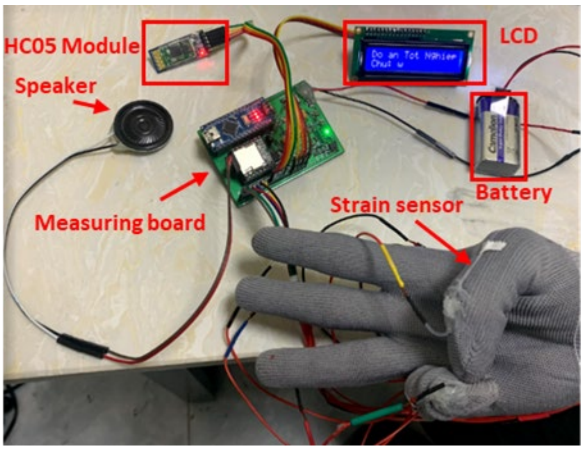


Fig. 2. The actual inplemented sign language reconition system before packaging

Image of the actual implemented system is shown in Fig. 2. A 9V battery is used as the supplied power for the whole system. It makes the system more safe for users. The measuring circuit is designed on and fabricated by many layer printed circuit technology. Additionally, a mini speaker and a LCD 1602 screen are also connected directly to the system to display the letter in place. The train sensors are attached on the glove by silicone glue to make sure that they do not change their position as the fingers moving.

B. Ionic Liquid Strain Sensor

Finger gestures are exploited through strain sensors located on the back of fingers. The prototypes of the proposed strain sensor are shown in Fig. 3(a). The proposed sensor consists of a high flexibility silicone, manufactured by AS ONE Corp., fully filled with a mixture of water, sodium chloride 99.5% and glycerin 99.0% (Xilong Scientific Ltd.). The mechanical characteristics of the silicone tube material are shown in Table I. Biocompatible glycerin is used to increase the viscosity of the liquid and prevent corrosion of the electrodes. Gold-coated electrodes are inserted at two ends of the tube to make contact with the liquid. Silicone glue is applied to the interface between the electrodes and the rubber tube for leaking prevention purpose.

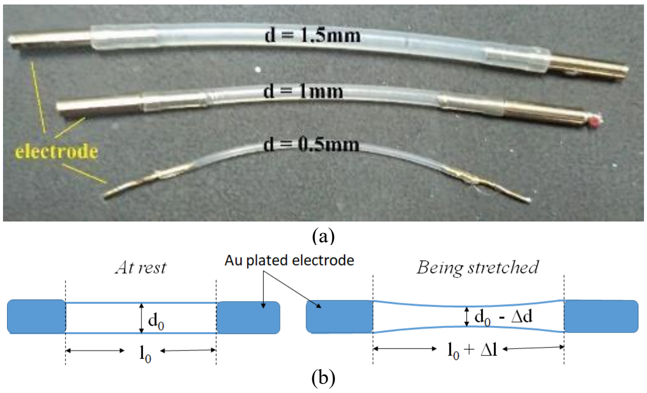


Fig. 3. Self-developed ionic-based strain sensor. (a) Fabricated prototypes of ionic liquid resistance strain sensor (b) Principle of the fluidic strain sensor, showing the geometry of the sensor at rest and when being stretched.

TABLE I. MECHANICAL PARAMETERS OF THE SILICONE TUBE

Parameter	Value
Hardness Type A	56
Tensile strength MPa [kg f/cm2]	9.51
Stretching [%]	460
Tear strength N/mm [kg f/cm]	20.6
Thermal conductivity [W/(m・k)]	~ 0.2

When an external force is applied, the sensor shape deforms resulting in an increase in length to $(l_0 + \Delta l)$ and a decrease in tube diameter $(d_0 - \Delta d)$ as shown in Fig. 3b. These geometrical changes vary the resistance of the sensor. The sensor then works as a strain gauge, where the resistance of mixture (R_s) will increase when being stretched. Resistance change can be measured by applying a current source to the resistor and measure the voltage drop. However, with this ionic liquid resistive sensor, using the DC causes electrolysis at the two electrodes that can destroy the sensor.

Furthermore, the parasitic capacitance between the electrode and the conducting liquid makes the measurement unstable. Therefore, an AC source is utilized instead of the DC current source in this study to improve the accuracy of the measurement. The sensitivity to strain expressed quantitatively as the gauge factor (GF) is defined as (ΔR/R0)/ε were characterized. Here, ΔR/R0 is the relative resistance change, R0 is the resistance at 0% strain, R is the resistance under stretch and ε is the applied strain. Results are presented in Fig. 4a. Silicone tube can be stretched up to over 50% and the resistance of the sensors increases linearly with the applied strain. The Gauge factor (GF) is calculated to be approximate 2.3. Five sensors with a diameter of 1mm are then attached on five fingers, as shown in the Fig. 4(b).

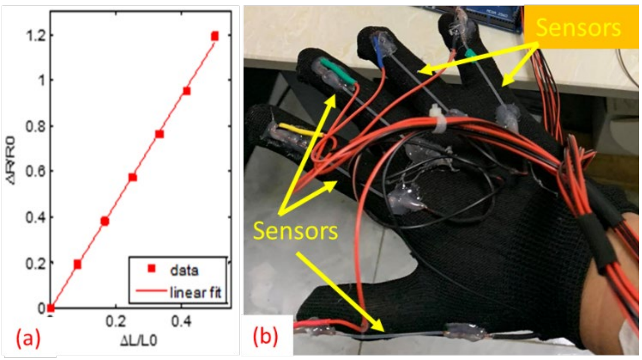


Fig. 4. Actual characteristic of the self-developed ionic-based strain sensor and assembly of the sensors on a glove (a) The sensitivity of fluidic strain sensor to strain (b) The located sensors on fingers

C. Signal processing

Signal from five sensors are read and processed in the central processor according to an algorithm shown in Fig. 5. The signal is passed through an average filter to reduce the amount of intensity variation between neighboring data points. Therefore, this filter make the signal more smooth and eliminate high frequency noise. Next, these data are analyzed and decoded whether they are letters. If they are a letter, they will be converted into a text format to display on the screen or the voice to play on a speaker. Otherwise, the program back to read new data from sensors and the process is started again.

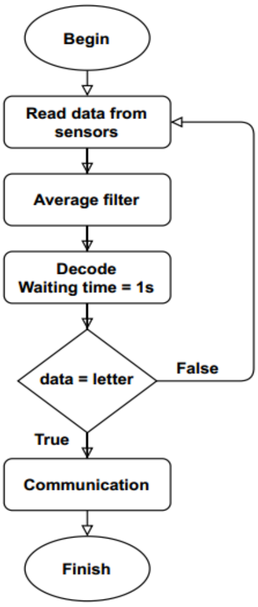
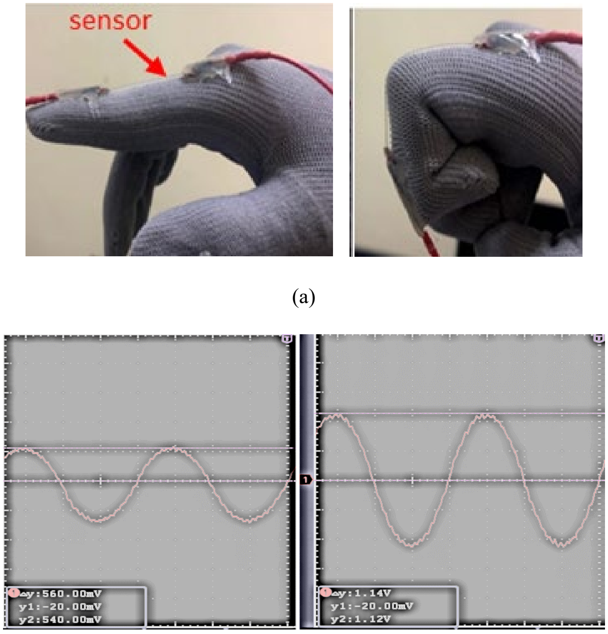


Fig. 5. Signal processing algorithm

For decoding method, there are three level of digitizing value for the proportion of changed resistance on the sensor ($\Delta R/R_0$) which are corresponding to each stage of finger open ('1'), intermediate ('2'), and fully closed ('3'). R_{max} is determined for full finger bending. Each level is assigned as '1' for the first 33 % of $\Delta R_{max}/R_0$, '2' for 34–67 % and '3' for the last 33 % with the largest resistance which is picked up at the fully closed finger. In fact, the system of 5 sensors with three levels for each sensor is able to distinguish 3^5 patterns, while the alphabet sign language ideally uses only 26 specific patterns among them. However, digitized sensor data provide multiple values for a certain letter in practical operation. For example, the hand gestures of the letters, A, B, and C are sufficiently represented by single sensor data of (12322), (21111), and (12222), respectively (table II).

III. RESULTS

After the sensor is fabricated and characterized, it is attached on a finger to investigate (Fig. 6a). The finger is initially straightened, then gradually folded to an angle of 120°. The signal on the sensor is shown in the Fig. 6b-c. It is clear that the voltage on the sensor increase significantly when the finger fold. At rest state, the finger is straightened, the amplitude of the signal on the sensor is 0.54V and it increase to 1.12V when the sensor fold about 120°.



(b) (c)

Fig. 6. Exxperimental results. A prototype of ionic liquid strain sensor on the finger (a) and the coresponding obtained signals on the strain sensor when the finger straighten (b) and fold an angel of 120 degrees (c).

In this study, there are 10 letters in American Sign Language system (ASL) be recognized, as shown in the table II. With each letter, the resistance change of sensors is investigated repeatedly about 10 times to obtain the average value. The sensors are attached in order from thumb to little finger. For example, with the letter 'A', it is signed by holding up your dominant hand in a fist, facing outward, with the thumb sticking up to the side of the fist. As can be seen the result table, the sensors which are attached on the index, middle, ring, little fingers have the highest proportion of resistance change because these fingers are strongly folded causing the sensor to be stretch, while the resistance of the sensor attached on the thumb is smaller, so it is only sticked up to the side of the fist. This experiment is conducted 10 times and then taken the average value. Besides, each data is digitized into values from 1 to 3 by the method mentioned in section II. It is clear that there is no duplication with the same digitized data for different letters. It also show that the strain sensor provides sufficient performance for the application of the sign language recognition. The hand sign can be convert into the letter by comparing to the reference set in the table II.

TABLE II. THE RESISTANCE CHANGE OF THE SENSORS WITH 10 DIFFERENT LETTERS

No.	Letter	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
		ΔR (%)	ΔR (%)	ΔR (%)	ΔR (%)	ΔR (%)
1	A	17.5	52.5	68.75	59.26	50
digitized data		1	2	3	2	2
2	B	42.5	7.5	3.13	0	6.25
digitized data		2	1	1	1	1
3	C	27.5	37.5	46.88	40.74	37.5
digitized data		1	2	2	2	2
4	D	42.5	2.5	46.88	44.44	45.83
digitized data		2	1	2	2	2
5	E	57.5	55	65.62	66.67	70.83
digitized data		2	2	2	2	3
6	F	32.5	47.5	15.63	18.52	29.17
digitized data		1	2	1	1	1
7	V	50	15	12.5	51.85	45.83
digitized data		2	1	1	2	2
8	W	50	15	6.25	11.11	54.17
digitized data		2	1	1	1	2
9	Y	7.5	60	62.5	59.26	27.08
digitized data		1	2	2	2	1
10	l	0	12.5	62.5	55.56	62.5
digitized data		1	1	2	2	2

After achieving the result table of resistance range on the sensors with each letter, an embedded program is built on the Arduino KIT to recognize automatically these letters. After that, we setup some experiments to evaluate the program. Experiments are investigated repeatedly about 15 times with each the letter to evaluate the accuracy of the system. The result shows the average accuracy rate is 98%, as shown in the table III. As can be seen from the table III, the majority of letters are recognized with the accuracy of 100%, while only 2 letters 'A' and 'C' have the lower accuracy, around 86% and 93%, respectively. Besides, the response time and the power of the device are also investigated. The response time is around 1.3 seconds, with the waiting time in the data processing algorithm being 1 second while the power of the device is 0.81W when the hand is at the rest and 1.71W when the fingers is working.

Furthermore, the applications are also developed on the smartphone and PC, as shown in the Fig.7. The apps on the smartphone is suitable to Android operating system while the apps on the PC can run stably on Window operating system. The software connects automatically to the hardware system through HC05 Bluetooth module. As can be seen from the user faces, there is a hand shape in the center of the display. It synchronized with hand gestures that user present. Besides, the letter is shown on a textbox below the hand shape and played on the speaker of the smartphone or PC. These things make it easy for opposite people to recognize the letter that the user wants to convey.

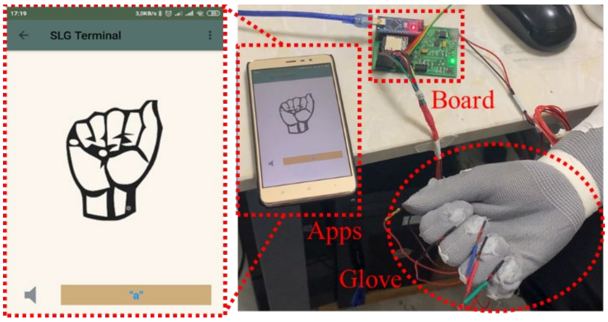


Fig. 7. Software interface on the smartphone

TABLE III. EXPERIMENT RESULTS WITH 10 DISTINGUISHED LETTERS

No.	Letter	Correct	Error	Accuracy (%)
1	A	13	2	86.67
2	B	15	0	100.00
3	C	14	1	93.33
4	D	15	0	100.00
5	E	15	0	100.00
6	F	15	0	100.00
7	V	15	0	100.00
8	W	15	0	100.00
9	Y	15	0	100.00
10	L	15	0	100.00
Total		**147/150**	**3**	**98.00**

IV. CONCLUSIONS

A system has been developed to recognize sign language by attaching five strain sensors on the glove fingers. The system can translate sign language into voice speech and text. The results showed that the system could detect 10 letters in ASL table with high accuracy (98%) and low energy. Moreover, apps on smartphone and PC were also built and connected to the system to display the letters that user want to convey. In future work, the proposed system can be extended to recognize fully letters and integrated some machine learning algorithm to rise the accuracy of the system.

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