Glove-Based Hand Gesture Recognition Sign Language Translator using Capacitive Touch Sensor

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***Abstract*—The sign language translator is a bridge between those who comprehend sign languages and those who do not, which is the majority of humanity. However, conventional signal language translators are bulky and expensive, limiting their wide adoption. In this paper, we present a gesture recognition glove based on charge-transfer touch sensors for the translation of the American Sign Language. The device is portable and can be implemented with low-cost hardware. The prototype recognizes gestures for the numbers 0 to 9 and the 26 English alphabets, A to Z. The glove experimentally achieved, based on 1080 trials, an overall detection accuracies of over 92 %, which is comparable with current high-end counterparts. The proposed device is expected to bridge the communication gap between the hearing and speech impaired and members of the general public.**

***Keywords*—Glove, gesture recognition, sign language translator, capacitive sensor, portable**

I. INTRODUCTION

One million people worldwide severely lack the ability to hear or speak [1]. Due to learning disabilities, they are often not able to communicate with the general public through conventional means, thus resorting to the use of sign languages. As the majority of healthy people have little or no understanding of sign languages, it is a challenge for the deaf and mute to effectively communicate with the people they meet throughout their daily lives. Sign language translators that are commercially available are typically limited in portability. The sophistication employed in detecting hand gestures requires heavy computations and associated energy storage, rendering these devices expensive and bulky, unsuitable of in-field applications.

Several major demonstrations of sign language recognition devices have been reported. Early gesture recognition devices operate through image recognition, which have suffered from poor accuracy. Ren et al. [1] attempts to circumvent this problem by translating small movements within a video into a time-series curve, which improves accuracy in the expense of heavy data processing. The use of flex sensors coupled with accelerometers or gyroscopes have been widely adopted for gesture recognition gloves.

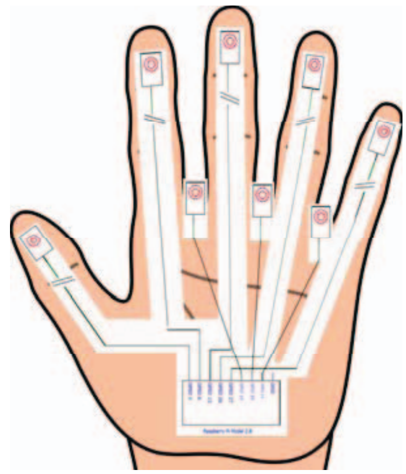

Fig. 1: Conceptual view of the gesture recognition glove consisting touch sensors and a processing unit.

The incorporation of flex sensors serves mainly to differentiate between many gestures that involve a certain ‘degree of bend’ of their finger. Several groups [2], [3], [4], [5] & [9] have implemented such sensors, which determine gestures based on the resistance of the flex sensor strip. In [3], the sensor incorporates five flex sensors mounted atop each finger. As the flex sensors are bent, the resistance across the sensor changes. The sensor achieved low hardware complexity. However, as the each user has a slightly different geometry, consistency across users is difficult to maintain.

Rather than implementing gesture recognition devices with variable resistors or recognition based on an analog input, the design in [6] employs a switch-based, binary system. Making use of light-emitting diodes for each of the 5 sensors mounted on the finger tips, the glove is able to interpret the position of each finger as a binary ‘1’ and ‘0’ when the finger is unbent and bent, respectively. In [7], a Greek sign language translator is presented based on a device that measures the degree of flex in the tendons. The device achieves a mean reported accuracy of 93 %. However, the wrist mounted device causes strain to the user. In [8], a piezo-resistive sensor based glove system is reported, based on a piezo resistive polymer that can be used to detect the degree of bend in the fingers. Unlike flex sensors mounted atop the palms, the sensors placed between the finger joints can be used to recognize the posture of individual finger segments, allowing more precise readings. However, the inelasticity of the glove posts accuracy issues. Although there have been key advancements in wearable gesture recognition systems, low portability, poor accuracy, and the need for a long calibration process between users still remain a challenge.

In this paper, we present a gesture recognition glove based on charge-transfer touch sensors for the translation of the American Sign Language. The device is portable and can be implemented with low-cost hardware. The glove employs a binary detection system that consists of a set of digital touch sensors rather than the analog signals from variable resistor, thus achieving good recognition accuracy. Hand gestures cause capacitive touch sensors to be selectively activated. This combination of activated sensors is subsequently interpreted as characters, which can be further made into sentences. The proposed device implements the recognition of all 26 English alphabets and 10 digitals signed in the American Sign Language (ASL).

II. Gesture Recognition and Glove Design

A. Gesture Recognition

Gesture recognition is performed through the use of 8 independent capacitive touch sensors, which output binary ON/OFF signals. As depicted in Fig. 1, five sensors are placed at the fingertips (T0–T4) and three additional sensors (R1-R3) are placed between the index, middle, ring and pinky fingers, respectively. The capacitive sensors are triggered when they are brought within 1.6 mm of human skin. Since the sensors are also triggered by conductive material and materials with a dielectric constant lower than that of human skin, a polymer type material has been chosen for the fabrication of the glove. Further, the glove is made thin enough to ensure that, when a part of the hand wearing the glove is brought near the sensor, such as when two fingers touches, the sensor can detect the skin underneath. For gesture recognition of the American Sign Language, the letters A through Z and numbers 0 to 9 are mapped to specific combinations of the 8 sensors, as shown in Fig. 2. The advantage of using combinations of binary sensor signals is that it is unambiguous. It is relatively easy to determine which sensors are active during a gesture and is unlikely that a gesture is misrecognized.

III. Touch Sensors and Data Processor

A. The PIC-116 Touch sensor

Each of the eight touch sensors is implemented using the PIC-116 capacitive sensor module. Fig. 3 depicts the schematic of the PIC module, which has a QT100 capacitive sensor integrated circuit (Quantum Technologies) as its core.

Gesture	Sensors Activated	Gesture	Sensors Activated	Gesture	Sensors Activated
0	All	C	R1-R3	O	T0, T1 & R1-R3
1	T0, T2-T4 & R2, R3	D	T0, T2, T3 & R2, R3	P	T3, T4 & R2, R3
2	T0, T3, T4 & R3	E	T1, T2 & R1-R3	Q	T2-T4 & R1, R2
3	T0, T4	F	T0	R	T0, T2-T4 & R3
4	T0	G	T2 -T4 & R1-R3	S	All
5	N.A	H	T3, T4 & R1-R3	T	T0, T2-T4 & R1-R3
6	T1-T3 & R1, R2	I	T1-T3 & R1, R2	U	T0, T3, T4 & R1, R3
7	T2-T4 & R2, R3	J	T0, T3 & R1, R2	V	T0, T3, T4 & R3
8	T3, T4 & R3	K	T0, T3 & R1- R3	W	T0, T4
9	T4	L	T3 & R1- R3	X	T2 & R2, R3
A	T1-T4 & R1-R3	M	T0, T4 & R1, R2	Y	T2, T3 & R1,R2
B	T0 & R1-R3	N	T0, T3, T4 & R1, R3	Z	T0, T2-T4 & R2, R3

Fig. 2. Table mapping activated sensor combination and intended gesture

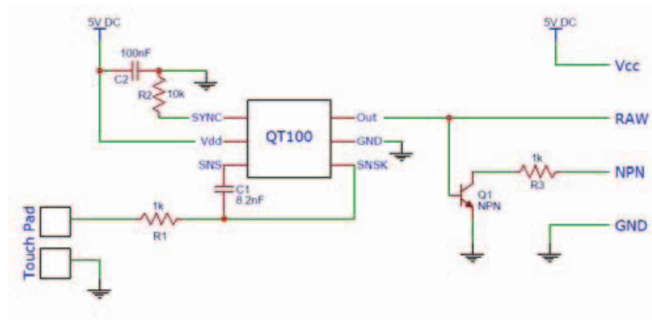

Fig 3: Circuit schematic of the PIC-116 touch sensor module.

A tradeoff between the sensitivity and the response time can be achieved by varying the value of the capacitor C1 in Fig. 3. The PIC module is also equipped with several output terminals, for example, a direct output terminal 'RAW' and a reverse input terminal 'NPN'. The latter is used so that, when the capacitive sensing electrode of the QT100 is activated, the QT100 output drives the NPN transistor, which serves as an output driver. The PIC module outputs 0 V and 1 V for logic low and high, respectively. A high logic level corresponds to the recognition of touch.

The QT100 is capable of acquiring signals from its sense electrodes every 5 ms. In addition, the QT100 is equipped to conduct drift compensation, noise cancellation, and self-calibration, which renders touch-sensing highly robust. The QT100 has three main components: a sense electrode and a sample-and-hold. The QT100 acts as a projection capacitance sensor, so a higher sensitivity means a greater projection distance or proximity detection distance. Signal acquisition is done mainly through a series of charge bursts.

In order to regulate and manage power consumption, the QT100 features several power modes such as sleep mode, fast mode, SYNC mode, and low power (LP) mode. For low-power operation, the prototype is operated in LP mode most of the time. In LP mode, charge bursts are timed 70 ms apart during sleep. When a possible input signal is encountered, the device activates a spike detection circuit that acts as a consensus filter. Each detection is resolved 4 times in consecutive order.

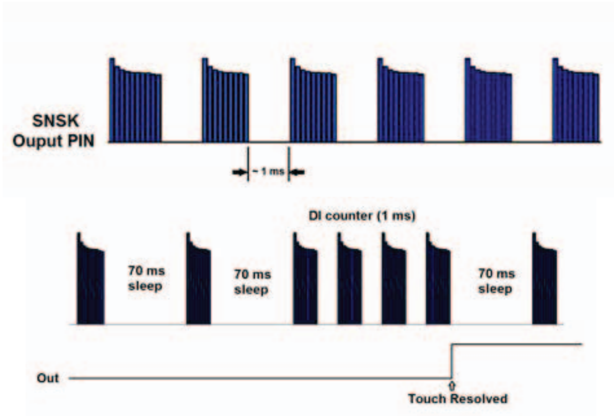

Fig 4: Timing of charge bursts at high (top) and low (bottom) SYNC states.

During this period, the device switches to fast mode to resolve possible touches quicker. If an input spike is indeed detected, a high out signal is generated. The system then returns to sleep mode. The timing diagram is depicted in Fig. 4

Drift compensation and forced recalibration are another two central aspects of the QT100 device. The former is focused on readjusting the QT100 reference level to account for gradual changes in capacitance values of C1 over time. This mechanism also allows the device to adapt to sudden changes in the environment, like an obstruction over the electrode. Drift compensation ceases when a legitimate touch is observed and it compensates faster for decreasing signals, for example, when an object is detected to be moving away from the pad. Recalibration is performed via either a full reboot of the sensor or through a 'max on' system. If the input signal is held 'high' for 60 consecutive seconds, the sensor is designed to ignore this signal and outputs a 'low' signal instead.

A DC voltage source of 4.5 V is supplied to all the sensors. Although the sensors are capable of operating at a lower voltage of 1.8 V, a higher supply voltage has been chosen to ensure that the voltage seen across the RAW and ground pins excess 3.3 V, the detection threshold for subsequent signal processing.

B. Analog-to-Digital Conversion

Binary data from the touch sensors is transmitted to integrated analog-to-digital converters (ADCs) of the RPi. The sensors are connected in parallel, via the RAW terminal to the GPIO pins of the Raspberry Pi.

C. Firmware and Data Processing

The main function of the firmware is to recognize the gestures, i.e. the combinations of binary sensor outputs. Recognition is performed via a look up process. The firmware is run on the Raspberry Pi Model 2, which is powered by a low-power ARM v7 core.

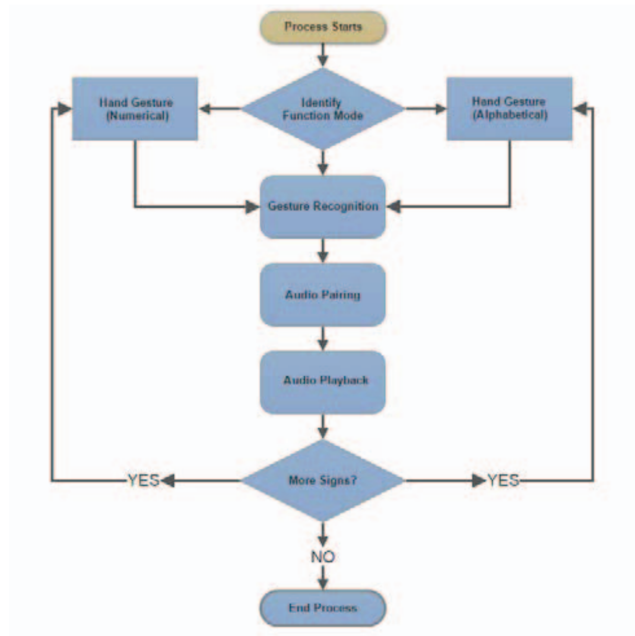

Fig. 5: Flowchart of firmware execution

The program consists of approximately 300 lines of code, written using Python 3.0 under the Linux development environment. Fig. 5 depicts the flow of program execution. The program contains supporting functions such as hardware initialization, analog-to-digital conversion, gesture recognition via look-up, and audio playback. Upon initializing, the program prompts the user for the type of character to be inputted. The user choice, either numbers or alphabets, is determined by a switch. Since numbers and alphabets share many of the common gestures, the two types are handled separately to improve recognition accuracy.

In order to allow the user sufficient time to complete the gesture, a 3 second countdown is implemented before each gesture is read. The length of such a countdown can be modified by the user. After the gesture is acquired and confirmed to be valid by the RPi firmware, the RPi proceeds to look up and playback the corresponding audio track.

IV. RESULTS

The RPi-based glove prototype has short start-up and response times. The prototype is able process a recognition in 0.7 s, with most processing time spent on loading the audio file. Fig. 6 depicts photographs of gestures for the American Signal Language for the alphabets 'A' and 'B'. Fig. 7 depicts experimental results of gesture recognition tests. Based on 36 possible gestures (A-Z, 0-1), 30 trials each, a total of 1080 trials produce an overall accuracy of over 92 %.

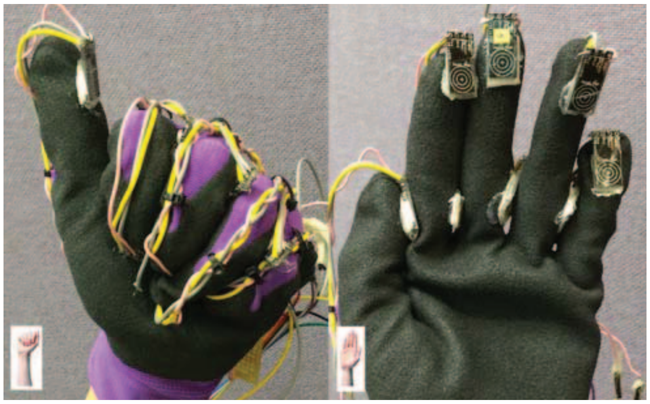

Fig. 6: Photographs of gestures for the American Signal Language for the alphabets ‘A’ (left) and ‘B’ (right).

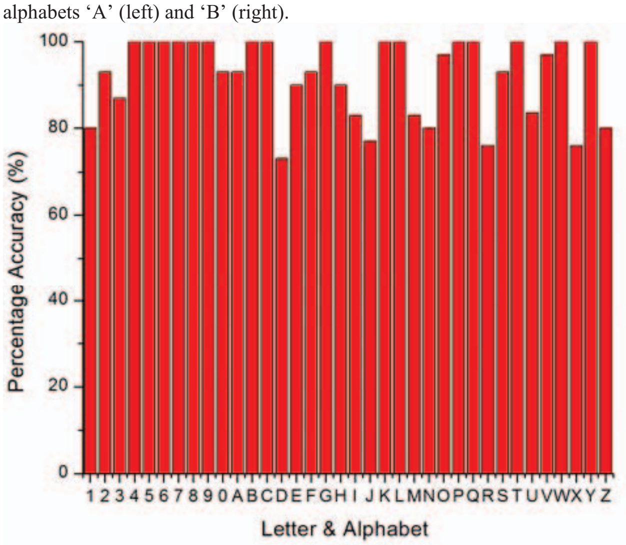

Fig. 7: Gesture recognition test for each number and alphabet of the American Sign Language. A total of 1080 trials (30 trials per gesture, 36 possible gestures) resulted in an overall accuracy of 92 %.

The high accuracy achieved is attributed to the unambiguous binary detection method employed and is comparable to high-end counterparts.

V. Conclusion

In this paper, we present a gesture recognition glove based on charge-transfer touch sensors for the translation of the American Sign Language. The device is portable and can be implemented with low-cost hardware. The prototype employs a set of capacitive touch sensors and the Raspberry Pi embedded system to recognize and translate hand gestures into sound. Through 1080 trials, the prototype achieves an accuracy of 92 %. The proposed technology is expected to vastly expand the audience to with whom to communicate for the hearing and speech impaired.

Acknowledgment

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