A review of factors that impact the design of a glove based wearable devices

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ABSTRACT

Loss of the capability to talk or hear applies psychological and social effects on the affected individuals due to the absence of appropriate interaction. Sign Language is used by such individuals to assist them in communicating with each other. The paper aims to report details of various aspects of wearable healthcare technologies designed in recent years based on the aim of the study, the types of technologies being used, accuracy of the system designed, data collection and storage methods, technology used to accomplish the task, limitations and future research suggested for the study. The aim of the study is to compare the differences between the papers. There is also comparison of technology used to determine which wearable device is better, which is also done with the help of accuracy. The limitations and future research help in determining how the wearable devices can be improved. A systematic review was performed based on a search of the literature. A total of 23 articles were retrieved. The articles are study and design of various wearable devices, mainly the glove-based device, to help you learn the sign language.

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1. INTRODUCTION

Living in the modern era of computerized world, where everything is straightforward and basic, a chunk of this world is losing the advantages this age has to offer [1]. The capacity to talk or the potency of speech is something we always underestimate. It is one of the best and incredible ways of sharing thoughts and feelings. It facilitates the communication with other individuals. Deafness is characterized as a level of hearing loss with the end goal that an individual cannot comprehend speech even when the sound is loud. As indicated by the World Health Organization (WHO), around 466 million individuals have hearing loss, 34 million of those are kids. The WHO additionally assessed that more than 900 million individuals will have this disability by 2050. There are a few reasons for hearing loss: hereditary problems, certain contagious illnesses, complications at birth, chronic ear infections, the utilization of specific drugs, exposure to extreme noise and ageing. This communication boundary unfavorably influences the lives and social connections of deaf individuals [2].

Human gestures are an effective and amazing method of communication. These are used to express a persons' emotions. A sign language is a language that utilizes manual gestures to pass on important information, instead of using speech. Nonetheless, there are interaction hindrances between hearing individuals and deaf people because deaf people will be unable to talk and hear or that hearing people will be unable to use sign to express themselves. This communication disparity can have an adverse effect on the lives of the deaf people. Two customary methods of communication between deaf people and hearing people who do not comprehend gesture-based communication: through mediators or text.

Innovation has diminished this mismatch through procedures that converts gesture-based communication into speech. These frameworks can be extensively ordered in the sorts of system, that can be used to change over sign language into speech. These are glove-based framework and vision-based framework. In glove-based frameworks, an individual sign's while conversing is transferred to the personal computer (PC). The real time sign is matched with the data set that contains all the signs, that were added at first to the framework. After comparing with the right sign, the information is passed onto text to sound converter, where the information is changed over to sound from sign. While the vision-based framework uses camera to recognize the gestures made by the hand and the body. However, vision-based framework requires lot of processing on the image such as color segmentation, image filtering and boundary detection.

This study tries to review the sign language gloves by doing a comprehensive assessment and evaluation based on a comprehensive synthesis of sensor glove papers. We present this thorough review that highlights the important achievements, sensor positioning, accuracy, limitations, methodology used, time taken to process and stress the challenges and prospects for this developing area of research.

2. METHOD

This study offers a methodical analysis of literature centered on the smart gloves for mute individuals. Several evolving ideas have been considered to enhance an insight of advances in the information on this crucial issue. This study tries to connect this disparity in the literature by doing a comprehensive assessment and evaluation based on a comprehensive synthesis of sensor glove associated research published. The following are a synopsis of the key opinions evolving from this literature assessment,

- Sensors used
- Sensor positioning
- Sign language
- Accuracy and efficiency of the system
- Time taken to process
- Limitations
- Methodology used

This paper categorized relevant articles by using an approach called keyword search. Various keywords were found and explored on IEEE explore. The main aim of this research is to understand the current research level on sensor gloves that can be used to interpret sign language. After rummaging through IEEE explore, 23 editorials were found that met the benchmarks for this analysis. All the articles were comprehensively reviewed by the authors to discover familiar factors. These factors were associated to find the differences in each article. The key aim of the article was also uncovered when processing these articles.

The results section is divided into 3 sections that are aim of articles, sensors, and feature comparison. In aim of articles, the major goal of the papers is discussed. While in sensors, comparison is done between the sensors used in these gloves and what impact that has on the result. And finally, in feature comparison, analysis is done to differentiate the differences in the papers that are achieving the same outcome.

3. RESULTS AND DISCUSSION

Several articles that have been reviewed by the authors have a similar main goal that is to design the glove that can translate the sign language into text. The majority of articles use flex and accelerometer to identify gestures. However, some of them use different types of gloves like touch sensor glove and surface electromyography (sEMG). These gestures are then either converted to text or to speech. To convert the gestures into meaningful data the articles have used various approaches like machine learning, database and different algorithms.

A good number of articles used microcontroller to process the sensor data, by dividing the sensor values into ranges for each gesture [3] and [4]. However, this methodology could cause error when the sensors are not in range [1], [5], [6] and [7]. A machine learning algorithm was used to determine the gesture in some of the articles [2] and [8]. While some use lookup table to determine the gestures [9]–[11], and [12], the article [13] and [14] used a data segmentation method. Data segmentation is based on a threshold-based method to extract 21 features for each data segment. As the classification model, the authors used the multivariate Gaussian distribution with diagonal covariance matrix. The multi-objective Bayesian framework for feature selection (BFFS) is implemented, with two objectives being discriminability power and fault tolerance maximization, to improve the recognition accuracy and reduce the model complexity by selecting a set of the 21 features. Natesh *et al.* [10] designed a glove for eight different sign languages. They were

Australian sign language (AUSLAN), British sign language (BSL), New Zealand sign language (NZSL), Indian sign language (ISL), deaf blind sign language (DBSL), Czech sign language (CSL), British, Australian and New Zealand sign language (BANZSL) and standard manual sign language (SMSL).

The authors in [15] and [16] used sEMG to get the data, which was processed for segmentation. After segmentation, features were extracted. This was done for the inertial sensors and static sensors. Then both these features were cascaded to select the best subset of the feature. After determining the subset, it was passed through classification model to recognize the gesture.

In [17] and [18] features were extracted from the sensors. These features were passed through a support vector machines (SVM) based classifier to recognize the gesture made. In [19] and [20] gesture recognition algorithm is devised which checks for contact sensor if they provide a similar gesture. if the gesture is not found, the code looks for any resemblance regarding the flex sensors. These two stages can determine almost all the gesture except the dynamic ones. To determine the dynamic gestures the inertial sensor is used. In [21] and [22] no dynamic gestures were recognized as the glove could only recognize static gestures. To process the gesture, three layers of nodes were used. The first layer hard 7 nodes which were the values from the seven sensors. These 7 nodes were converted into 52 nodes by applying weight on them. The final layer had 26 nodes; each node denotes to an alphabet. The authors in [23]–[31] and [32] stored the sensor values into a file which was loaded into a LabView program. This program receives the values from the file and matches this data with gestures close to American sign language (ASL) gestures. In article [33]–[36] and [37], the gestures for each letter were processed by storing the voltage levels of the sensors into the database. To determine a gesture, the program compares the sensor values to the ones in the database.

In [38] and [39], a learning mode is used to train the system. the system stores values from the gloves in a comma-separated values (CSV) file 20 times. These readings are used to evaluate the range of each gesture for this specific user. Whenever the user starts communicating using the glove, the program uses the sensor values and look for the value of the gesture made by the user in the CSV file. The authors in [40] and [41] used an SVM base classifier. The sensor values for each gesture are used to train the SVM classifier. The model generated is used to predict the gesture made. In [42], [43] and [44], online gesture recognition model is proposed which consists of two parts: segmentation with threshold-based and classification with a probabilistic model. The system determines the sensor values and uses the threshold to determine which gesture it is. To validate the gesture probabilistic model is used, a very inefficient method was used in [35], [45] and [46], where the gestures were recorded manually. The user has to make the gesture and select the alphabet. This solution will not detect the gesture if there is a slight difference in the sensor readings. In [47]–[49] and [50] the sensor values were obtained and passed through multiple algorithms to evaluate the accuracy. The glove was able to achieve more accuracy than previous experiments. Figure 1 shows the overall design for sign language recognition for most systems. Figure 1 shows the overall design for sign language recognition for most systems. The articles presented in this review have been summarized in Table 1 (APPENDIX).

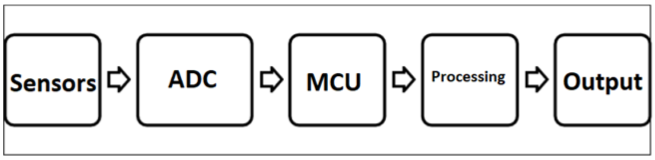

Figure 1. Block diagram of common sign language recognition system

4. CONCLUSION

This review was centered on the characteristics of the Glove based wearable devices, it uncovered numerous concepts and how they are utilized. The reach and complexity of the articles highlights the algorithms and sensors used to develop these gloves. Most of the gloves did not have an accelerometer to get the dynamic gestures. They have used different methodology. However, this methodology of using flex to identify dynamic gestures could produce ambiguous results. Some of the gloves could not process data in real-time, which could be a real drawback as the application is to talk in real-time. Some gloves required training to be used, which is a problem when the glove is constantly switched between multiple users. Various articles did not give adequate information about their test, test plan and accuracy of the system. Certain gloves had a delay in reading the gestures, so the hand should stay still for a short period of time before moving to the next gesture to allow for the system to interpret it. While some places delay was introduced to process the data. This is very inconvenient as the communication speed would be quite slow. In terms of accuracy, half of the papers reviewed achieved an accuracy of 90% or more. While six of them had accuracy of 70% to 90%. Some paper had multiple accuracies for different algorithm or design. One of the major factors in getting better accuracy was use of either contact sensors or accelerometer to get dynamic gestures. The other factor that influenced accuracy was the algorithm used. The algorithms with higher accuracy were usually the ones with machine learning algorithm or using different algorithms like k-nearest neighbors (k-NN), segmentation and gesture recognition. The ones with the lower accuracies were the one which used raw values to determine the gesture. Another factor was the hand size that could have an impact on the accuracy. If the size of the hand is big, it would mean that flex sensors would bend properly. Proper bending of flex sensors would create a higher range of values which would increase the accuracy. Moreover, some of the papers were not able to determine the accuracy or did not mention it in the paper. Future improvements can be done on this topic, by designing the glove based on the user to yield better results or compare different hand sizes to know the level of inaccuracy. This could be helpful in determining whether glove will work with others or not. Use of different sensors could be another improvement, this could help in making a more flexible glove.

APPENDIX

Table 1. Feature comparison

Paper	Sign Language	Sensor positioning/ Components used	Accuracy/ Efficiency	Method used	Time taken to process the input	limitations	Future study proposed
1	ASL 26 alphabets	Four flex sensors.	Not mentioned	To develop a cheap sensory data glove to help disabled people communicating	Not mentioned	Accuracy limited by size of the hand	Making the glove wireless. Addition of accelerometer. Speaker to listen to the converted gestures.
2	ASL 26 alphabets and 15 words.	Two flex sensors are used for thumb and pinky, and a pair of sensors for each other finger	95%	A machine learning algorithm	Not mentioned	Not mentioned	Increase in the size of database. Integrating the glove with other devices at home.
5	ASL 26 alphabets.	The flex sensors and the accelerometer sewed to a white cotton glove	74%	Five flex sensors, an GY61 accelerometer, Arduino Mega 2560, micro-SD card reader module, liquid crystal display (LCD). A gesture recognition algorithm	0.74 seconds to translate the gesture into text and speech	Soldering defect on thumb's flex sensor	Wireless gloves.
9	American sign language (ASL) and the Pakistan sign language (PKL)	A leather glove with 11 flex sensors, one for each finger (5) and one for each abduction (4). Two extra sensors are used for measuring the roll and pitch of the wrist.	90%	Lookup table, template matching along with statistical pattern recognition	Not mentioned	Only static gestures.	Improve accuracy of the system
13	ASL 26 alphabets, full stop, space, and resting (fully-stretch finger). Total of 29 gestures.	Five flex sensors connected in parallel with five contact sensors and an accelerometer. There are also seven fabric electrical contacts, two positives, placed on the index and thumb fingers, and five negatives, placed on lower, top, front of the middle finger, index finger, and pinky finger.	76.1% for the Multivariate Gaussian distribution. 77.9% for the Multi-objective Bayesian framework for feature selection (BFFS)	Data segmentation is based on a threshold-based method. Multivariate Gaussian distribution with diagonal covariance matrix for classification. The multi-objective Bayesian framework for feature selection (BFFS) is implemented to reduce complexity.	Not mentioned	Ambiguity in gestures lea dig to error in determining the letter.	Extra contact sensors to remove ambiguity.

Table 1. Feature comparison *(continue…)*

Paper	Sign Language	Sensor positioning/ Components used	Accuracy/ Efficiency	Method used	Time taken to process the input	limitations	Future study proposed
33	ASL 26 alphabets.	Flex and contact sensor the length of the fingers	91.54%	It uses the k-nearest neighbors (k-NN) algorithm to identify the alphabets. Database used to store various alphabets.	500ms. Data segmentation was used to identify change in gesture.	Only identifies 26 alphabets.	Updating the system to identify words and sentences. Reduce the time taken to identify the alphabets to less than 500ms.
15	ASL SIGN 80 gestures	Four major muscle groups are chosen to place four channel sEMG electrodes: 1) extensor digitorum, 2) flexor carpi radialis longus, 3) extensor carpi radialis longus, and 4) extensor carpi ulnaris. The inertial measurement unit (IMU) sensor is worn on the wrist, where a smart watch is usually placed.	96%	The data collected from three sessions of the same subject are put together and a 10-fold cross validation is done for the data collected from each subject separately.	A quiet period of 2-3 s between gestures is required	Large number of gestured may be difficult to predict using the method suggested in this paper. Wearable inertial sensor and sEMG-based sign language recognition (SLR) system is that the facial expression is not captured.	The paper suggests that to recognize continuous sentence, a different segmentation technique or other possibility models should be considered.
3	ASL 26 Alphabets and 0-9 numbers	It uses 8 independent capacitive touch sensors. 5 placed at fingertips and 3 sensors placed between index, middle, ring and pinky fingers.	92%	Uuses python code and RPi firmware.	Recognizes alphabets within 0.7sec. There was a countdown of 3 sec between two gestures.	not mentioned	not mentioned
10	All eight sign languages AUSLAN, BSL, BANZL, NZSL, ISL, DBSL, CSL, SMSL	The glove consists of 9 flex and 8 contact sensors placed in appropriate positions on fingertips and flex sensors on the outer region of the fingers.	The system efficiency was found to be 80.06% in identification mode (IM) and was enhanced to 93.16% in enhanced identification mode (EIM)	The two subsystems interconnected through a pair of TIs' CC2541 bluetooth low energy (BLE) modules.	Gesture recognition system is 41.1 milliseconds in IM and 151.5 milliseconds in EIM. It is thus capable of recognizing 24 gestures per second in IM and 6 gestures per second in EIM	not mentioned	not mentioned
17	ASL 26 Alphabets	Five flex-sensors along the length on the outer surface of each finger. In case of the second version two additional pressure sensors were placed and on the left side of the first joint of the middle finger,	Accuracy Rate of 65.7% can be achieved without pressure sensors and 98.2% accuracy with pressure sensors on the middle finger.	The proposed system in this paper utilizes five flex-sensors, two pressure sensors, and a three-axis inertial motion sensor	10 sec for every letter with a 3s gap between two signs	not mentioned	Future work proposes design of a smaller sized printed circuit board, the inclusion of words and sentences at the sign language level, and instantly audible voice output.

Table 1. Feature comparison *(continue…)*

Paper	Sign Language	Sensor positioning/ Components used	Accuracy/ Efficiency	Method used	Time taken to process the input	limitations	Future study proposed
19	American sign language (ASL) 26 alphabets	Flex sensors are connected on the fingers (Dorsal side of hand). Contact sensors are connected at multiple places depending on the gestures. While the inertial sensor is connected on the tip of ring finger.	The system gave accuracy of 92 % on trained ASL testers while it should 81% on amateur testers.	Gesture recognition algorithm is used. First it checks the contact sensors and see if there is any equivalent gesture. Then it compares with flex sensor reading to refine the gestures. And finally, it uses inertial sensor to finalize the gesture.	Not mentioned	Not mentioned	Not mentioned
21	American sign language (ASL) 24 alphabets plus two punctuation symbols.	Seven sensor gloves are used. Five sensors are placed on fingers and thumb. One sensor is to measure the tilt while the last one is to measure the rotation	88%	Three-layer algorithm is used, first layer passes the raw sensor values to the second layer. Second layer has 52 nodes. It applies weight to the input and passes to the third layer. The third layer consists of 26 nodes, each node denoting one alphabet.	Sampling = 4 times per second. 0.75s required to determine the letter.	Does not have dynamic gestures. Or gestures with two hands.	Use of camera to determine sign using facial expressions. Use of speech engine to speak the text from the gestures. Extra sensors to determine the body language to aid in sign determination.
23	American sign language (ASL) 26 alphabets	Eighteen sensors are used on the glove. Two resistive bend sensors on each finger, four abduction sensors and sensors measuring thumb crossover, palm arch, wrist flexion and abduction.	90%	A Labview program collects data and saves it to a file. This data is analyzed and used to train neural network. While another program uses the data from glove to analyze the ASL sign. After determining the sign, the program plays the sign.	Cannot process real-time	Cannot process real-time	Development of wearable glove that recognizes and translate sign language to spoken English. And translating spoken English to sign language.
34	American sign language (ASL) 26 alphabets	It has six flex sensors placed on fingers, thumb and wrist, and three contact sensors placed on fore finger, middle finger and thumb.	83%	Every gesture has different voltage levels, the system compares voltage level from gesture made by the glove and identify the alphabet.	Not mentioned	Not mentioned	Not mentioned
38	American sign language (ASL) and Arabic sign language (ArSL)	Five flex sensors are placed on fingers and thumb. Inertial sensor mpu6050 is also connected.	Static = 95% Dynamic = 88%	The data is collected from the glove and processed using Arduino. And outputted using a graphical user interface (GUI) program made using python3.	1000ms.	Mismatches in words with similar gesture.	Use of contact sensors on the tip of the finger. Using a left-hand glove. Increasing the size of the glove. Making the system multilingual.

Table 1. Feature comparison *(continue…)*

Paper	Sign Language	Sensor positioning/ Components used	Accuracy/ Efficiency	Method used	Time taken to process the input	limitations	Future study proposed
24	American sign language (ASL) 26 alphabets	Five flex sensors are placed on fingers and thumb.	Not mentioned	The sensors give their raw values to data acquisition cards (DAQ) card and Lab view program. The program converts the letter to binary code. The binary code is then used to translate letters and words. The program then converts it to text and audio.	Not mentioned	Not mentioned	Replace flex sensor to increase efficiency. Make the glove wireless. Make the program standalone to make it portable.
25	American sign language (ASL) 26 alphabets	Five flex sensors are placed on fingers and thumb.	95%	The system determines the alphabets from the flex sensors, then uses accelerometer and contact sensors if the gesture is not found.	Not mentioned	Not mentioned	Add more sensors like gyroscope. Enhance speech synthesis. Wireless communication
26	Indian sign language	Five flex sensors are placed on fingers and thumb.	Limited by hand size	The sensors give their raw values to Arduino. The Arduino recognizes the gesture and outputs it to LCD screen and send it to Bluetooth module. A smartphone can be connected to the Bluetooth module to get the gesture recognized.	Not mentioned	The accuracy of the system is limited by the hand size. Smaller hands can be more accurate due to larger bend of the sensor. Does not have dynamic gestures.	Add more sensors to recognize full sign language.
27	American sign language (ASL) 26 alphabets	Five flex sensors are placed on fingers and thumb.	Not mentioned	The sensors give their raw values to Arduino nano. The Arduino nano transmit the data through transmitter to Arduino mega. The Arduino mega converts the signals into gesture and displays the gesture on LCD screen. Raspberry pi is used to play the sound of the sign recognized.	Not mentioned	Does not have dynamic gestures.	Increase scope by adding another glove
40	American sign language (ASL) and Indian sign language (ISL)	Five flex sensors of fingers and thumb and an MPU6050 sensor	ASL = 98.91% ISL = 100%	The data from the sensors is processed by feeding it into an SVM based classifier. After determining the gesture, the Arduino sends the data through Bluetooth which is played on speaker after processing it.	2s	Does not have all the gestures.	Increase number of sensors. Add additional glove.

Table 1. Feature comparison *(continue…)*

Paper	Sign Language	Sensor positioning/ Components used	Accuracy/ Efficiency	Method used	Time taken to process the input	limitations	Future study proposed
42	American sign language (ASL) 26 alphabets plus two punctuation symbols.	Flex sensors are connected on the fingers and thumb. While the inertial sensor is connected on the back of the hand.	73.6%	An online gesture recognition model is used which consists of two parts segmentation and classification. Segmentation is used to determine the gesture made and classification is done to form the sentences. The recognized gestures will be sent to the speaker after the sentence finishes.	0.5s	Less features that disrupt the accuracy	Compare each detected word with an extensive vocabulary set to increase efficiency.
35	American sign language (ASL) 26 alphabets	Flex sensors are placed on the fingers and thumb.	86%	The system has two modes, teach, and learn mode. In teach mode the user can store the gestures made, while in learn mode the user can check if the gesture made is correct or not.	3s	Not mentioned	Use of additional sensors and camera to aid in detection. Use of speech engine to play the translated text.
47	American sign language (ASL) 26 alphabets	Flex sensors are placed on the fingers and thumb.	98%	The data from the sensors is processed by comparing it to the existing voltage level to determine the gesture made. After recognizing the gesture, it's played on the mp3 player module.	Not mentioned	Not mentioned	Not mentioned

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