

Sign Language Interpreter Using Sensor Gloves with a Bluetooth-Connected Mobile Application: A Literature Survey

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Abstract: Sign language is the primary means of communication for many deaf and hard-of-hearing people, yet most hearing people do not understand it. Sensor-glove-based interpreters address this gap by converting finger and hand movements into text and speech. This paper surveys the literature on sign language interpretation using instrumented gloves, covering flex, inertial, contact, capacitive and electromyography sensing, recognition algorithms from template matching to neural networks, and wireless transfer to mobile devices over Bluetooth. A comparison of representative works, together with the research gaps identified, is presented to guide the design of a low-cost, portable glove that streams data over Bluetooth to a smartphone application for real-time text and voice output.

Keywords: Sign language recognition, sensor glove, flex sensor, Bluetooth, mobile application, gesture recognition, text-to-speech.

I. INTRODUCTION

Hearing loss affects a very large population; the World Health Organization estimates that hundreds of millions of people live with disabling hearing loss [1]. For many of them sign language is the natural language, but its use is largely limited to the deaf community and trained interpreters. This creates daily communication barriers in education, healthcare, public services and employment.

Automatic sign language interpretation is an application of gesture recognition [2]. Existing approaches fall into two groups: vision-based systems that analyse camera images, and sensor-based systems in which the signer wears an instrumented glove. Glove-based systems measure finger bending and hand motion directly, so they are not affected by lighting, background clutter or camera placement, and they can be built from inexpensive, portable components. With Bluetooth now available on virtually every smartphone, a glove can send its readings to a mobile application that performs recognition and presents the result as text and synthesised speech.

This paper reviews the literature relevant to such a system. Section II gives the technical background, Section III reviews earlier work, Section IV compares sensing technologies, Section V discusses research gaps, Section VI outlines a typical system architecture derived from the surveyed work, and Section VII concludes.

II. BACKGROUND

A. Vision-Based versus Sensor-Based Recognition

Early camera-based systems used hidden Markov models (HMMs) to recognise American Sign Language (ASL) from video; Starner et al. reported accuracies of about 92% with a desk-mounted camera and about 98% with a cap-mounted camera on a 40-word vocabulary [3], and Vogler and Metaxas combined HMMs with 3-D motion analysis [4]. Vision-based methods need no worn hardware but depend on illumination, background and camera position, and they raise privacy concerns. Sensor-based methods avoid these problems at the cost of requiring the user to wear a device.



Detailed reviews of glove-based and wearable-sensor systems are given in [5], [6] and [7], while a broader deep-learning-oriented survey is given in [8].

B. Sensing Elements in Gloves

Flex (bend) sensors fixed along each finger give a resistance that changes with bending angle and are the most common element in low-cost gloves. Inertial measurement units (IMUs), which combine accelerometers and gyroscopes, capture hand orientation and movement, which is needed for dynamic signs. Contact or pressure sensors detect finger-to-finger and finger-to-palm touches, and capacitive touch sensors serve a similar purpose [5]. Surface electromyography (sEMG) records muscle activity from the forearm and is usually combined with an IMU [7].

C. Wireless Transfer Using Bluetooth

A glove must transmit its data to a phone without cables. Bluetooth is well suited to this because it is available on all smartphones, needs no network infrastructure and has a short range matched to wearable use. Classic Bluetooth modules using the serial port profile are simple to interface with microcontrollers, whereas Bluetooth Low Energy (BLE) offers much lower power consumption through its characteristic-based data model, which is attractive for battery-powered gloves [9].

D. Mobile Application and Speech Output

On the smartphone, an application receives the sensor stream, applies a classification model or lookup, displays the recognised word or letter and uses the built-in text-to-speech engine for audio output. This moves heavy processing and the user interface off the glove, so the glove electronics can remain small and low-power.

III. LITERATURE REVIEW

A. Early Glove-Based Systems

One of the earliest efforts, the Talking Glove by Kramer and Leifer, used a glove with sensors to recognise the ASL manual alphabet and present it to deaf-blind and non-vocal users [10]. Fels and Hinton developed Glove-TalkII, in which neural networks map hand gestures, captured with a data glove and a position tracker, to control a speech synthesiser, demonstrating gesture-to-speech conversion [11]. Kadous used the low-cost Power Glove with instance-based learning to recognise a vocabulary of about 95 Auslan signs, showing that inexpensive hardware could support meaningful recognition even though its sensing was coarse [12].

B. Machine-Learning Methods on Glove Data

Mehdi and Khan applied a neural network to data from a sensor glove to recognise ASL letters, handling static hand shapes only [13]. Oz and Leu used a CyberGlove with a 3-D motion tracker and artificial neural networks to recognise ASL words, reporting high accuracy and showing that adding position information helps with signs that share a hand shape [14]. The accuracy of such systems is high, but research-grade gloves are expensive, which limits everyday use.

C. Multi-Sensor Fusion

Abhishek et al. combined flex sensors with capacitive touch sensors to separate ASL letters that are hard to tell apart from finger bending alone [15]. Wu et al. fused IMU and sEMG signals in a wearable system to recognise ASL signs in real time, reporting high accuracy in user-dependent tests, but the approach needs electrodes on the forearm [16]. Lee and Lee proposed a smart wearable hand device that fuses several sensor types for sign interpretation [17]. These studies agree that combining bend, motion and contact data gives better discrimination than any single sensor.

D. Advanced Wearable Sensors

Zhou et al. built a glove from stretchable sensor arrays and used machine learning for sign-to-speech translation, with recognition of several hundred signs and low latency, and showed sentence-level output [18]. This marks the state of the art in accuracy and vocabulary size, but depends on specialised fabrication that is hard to reproduce in a student or low-cost setting.

E. Wireless and Mobile Aspects

The reviews in [5] and [7] note that many glove prototypes still send data over a wired link to a PC, and that wireless gloves commonly use Bluetooth to a phone or computer for display and speech output. Published prototypes of this



kind typically pair flex sensors with a microcontroller and a Bluetooth module, but report small vocabularies, often letters or a few words, and limited testing across users. Reports on latency, battery life and power-saving strategies, such as BLE, are comparatively sparse [5], [9].

Author/Reference	Sensing / Technique	Scope	Remarks
[11] S. S. Fels and G. E. Hinton	Glove-TalkII; sensor glove with neural-network-based gesture-to-speech mapping	Gesture-to-speech control	Demonstrated gesture-driven speech synthesis using a neural network
[12] M. W. Kadous	PowerGlove with sensor-based learning	About 95 Auslan signs	Low-cost hardware; demonstrated recognition of a relatively large sign vocabulary
[13] S. A. Mehdi and Y. N. Khan	Sensor glove with neural-network recognition	ASL letters and hand gestures	Focused mainly on static hand shapes; demonstrated sensor-based sign recognition
[14] C. Oz and M. C. Leu	CyberGlove, 3-D tracker, and artificial neural network	ASL word recognition	Accurate recognition but requires relatively costly and complex hardware
[15] K. S. Abhishek, L. C. F. Qubeley, and D. Ho	Flex sensors and capacitive touch sensors	ASL alphabet	Improved separation and recognition of similar hand/finger configurations
[16] J. Wu, L. Sun, and R. Jafari	IMU and surface EMG (sEMG) sensor fusion	Real-time ASL word recognition	Provides richer motion and muscle information but requires forearm electrodes
[17] B. G. Lee and S. M. Lee	Multi-sensor fusion using wearable hand-device sensors	Sign language interpretation	Compact wearable approach combining multiple sensing modalities
[18] Z. Zhou et al.	Stretchable sensor arrays with machine-learning-based recognition	Several hundred signs; sign-to-speech translation	Large vocabulary and flexible sensing; requires specialized fabrication

IV. COMPARISON OF SENSING TECHNOLOGIES

Sensor	Measures	Strengths	Limitations
Flex sensor	Finger bending	Cheap, simple analogue read-out	Drift and wear; cannot sense hand motion
IMU	Orientation and motion	Captures dynamic signs; small	Needs filtering and calibration
Contact pressure /	Finger touches	Separates similar hand shapes	Adds wiring on fingertips
Capacitive touch	Touch contacts	No moving parts	Sensitive to moisture and noise



Sensor	Measures	Strengths	Limitations
sEMG	Muscle activity	Captures subtle forearm effort	Electrode placement, user dependent

The literature suggests that flex sensors alone suit static signs and letters, while a practical interpreter for words and phrases benefits from adding an IMU and, where hand shapes are similar, contact sensing [5], [15], [17].

V. RESEARCH GAPS AND CHALLENGES

Several gaps emerge from the survey. First, most work targets ASL, with comparatively little on regional languages such as Indian Sign Language, which also uses two-handed and non-manual features. Second, many prototypes recognise only letters or a small word set, and evaluation with few signers hides the effect of different hand sizes and signing styles [5], [7]. Third, sign language also uses facial expression and body posture, which a glove cannot capture. Fourth, calibration of flex sensors for each user remains a practical difficulty. Finally, there is little reporting on end-to-end latency, battery life and usability of the Bluetooth link and mobile application, even though these decide whether a system is usable in daily conversation.

VI. TYPICAL SYSTEM ARCHITECTURE

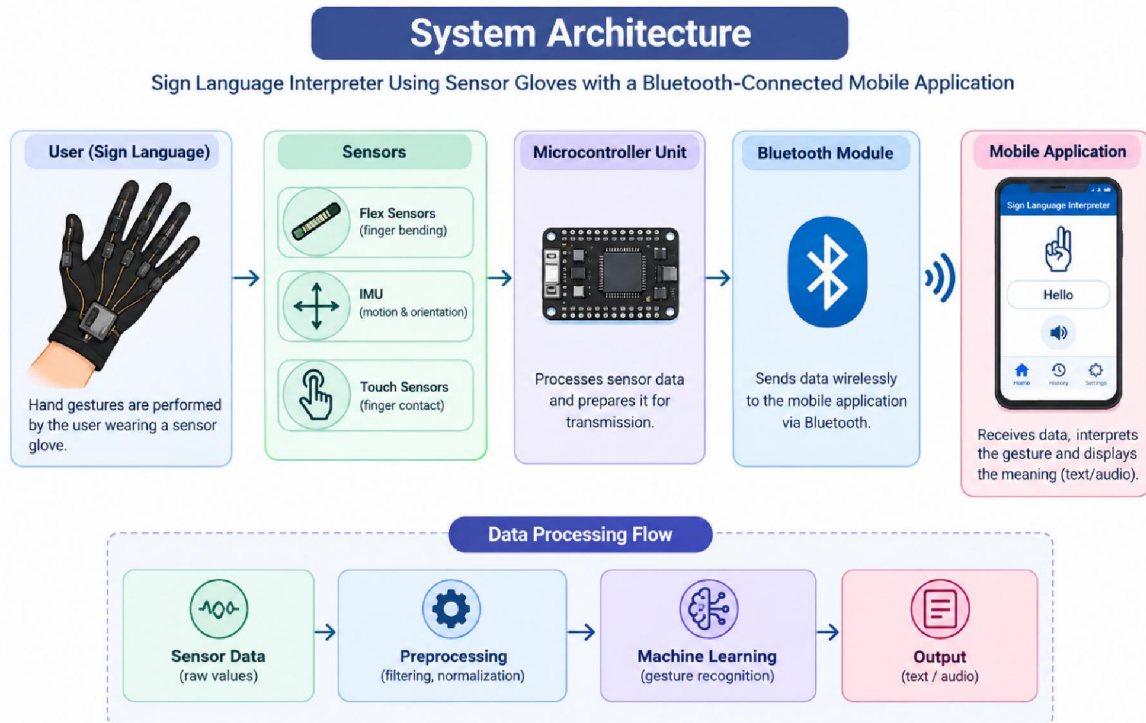


Fig. 1 Architecture of Sign Language Interpreter using Sensor Gloves with a Bluetooth-Connected Mobile Application From the surveyed work, a representative low-cost design has four blocks. (1) A glove with flex sensors on each finger and, optionally, an IMU and contact sensors. (2) A microcontroller that samples the sensors, filters the readings and packages them. (3) A Bluetooth module (classic or BLE) that streams the packets to the phone. (4) A mobile application that receives the data, runs a classifier or template matching, displays the recognised text and speaks it with text-to-speech. Training data are collected from several users, and the model can be refined in the app. This architecture follows the common pattern in [5], [7] and is presented as a design outline, not as the method of any single cited paper.



VII. CONCLUSION

Sensor gloves provide a robust and portable alternative to camera-based sign language recognition. The literature shows progress from early flex-sensor gloves to multi-sensor fusion and stretchable-sensor systems with large vocabularies, but low-cost Bluetooth-connected systems are still limited by small vocabularies, single-user testing and little attention to latency and power. A glove combining flex and motion sensing, a Bluetooth link to a smartphone application, and on-device text and speech output addresses the needs identified here, and future work should test it with multiple signers and regional sign languages.

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