Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 133 (2018) 55–62

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Robotics and Smart Manufacturing (RoSMa 2018)

Recognition of Sign Language Alphabets and Numbers based on Hand Kinematics using A Data Glove

Nayan M. Kakoty*, Manalee Dev Sharma

Embedded Systems and Robotics Lab, School of Engineering, Tezpur University, Tezpur - 784028, Assam, INDIA

Abstract

This paper reports real-time recognition of Indian and American sign language alphabets and numbers based on hand kinematics assessment. The finger and wrist joint angles were acquired using an indigenously developed data glove. The data set was for single handed Indian sign language alphabets (C, I, J, L, O, U, Y, W), American sign language alphabets (A to Z) and sign numbers (0 to 9). The data were pre-processed through a moving average filter and standardized feature scaling methods. The glove was able to measure the finger joint angles with an accuracy±standard deviation for metacarpophalangeal (MCP) joint±2.14°, proximal inter phalangeal (PIP) joint±1.73° and distal inter phalangeal (DIP) joint±1.49°, during flexion/extension and abduction/adduction movements. A radial basis function kernel support vector machine with 10-fold cross validation was used for recognition. An average recognition rate of 96.7% was achieved. Using a label matching and speech data base, the recognized alphabets and numbers were translated into speech.

© 2018 The Authors. Published by Elsevier Ltd.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0/)
Peer-review under responsibility of the scientific committee of the International Conference on Robotics and Smart Manufacturing.

Keywords: Finger kinematics; Sign language recognition; Data glove

1. Introduction

Sign language continues to be the preferred method of communication among the deaf and hearing-impaired. Advances in information technology have prompted the development of systems that can facilitate automatic translation of sign language into speech. Two methods viz., vision-based and glove-based systems [1] are in application for recognition of sign languages. Among these, most of the sign language recognition systems use vision-based systems. Unlike vision-based systems, glove-based systems allow one with the freedom for locomotion during the recognition process and is independent of the environmental lighting conditions [2]. This makes glove-based systems more useful for the user. Although research in sign language recognition using data-glove has made advances in recent years, currently available data-gloves are highly cost and very few of them have been explored for translation of sign language to speech.

* Corresponding author. Tel.: +91-03712-275263
E-mail address: nkakoty@tezu.ernet.in

1877-0509 © 2018 The Authors. Published by Elsevier Ltd.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0/)
Peer-review under responsibility of the scientific committee of the International Conference on Robotics and Smart Manufacturing.
10.1016/j.procs.2018.07.008

Starner and Pentland [3] were among the pioneers in reporting the recognition of sign language. A camera based real time tracking of hand gestures for recognition of American sign language (ASL) using Hidden Markov Model (HMM) have been reported. A British sign language recognition system is proposed in [4], wherein the hand shapes were described by a Histogram of Oriented Gradient (HOG) descriptor, and classification was using HMM. Sarkaleh et.al. [5] developed a Persian sign language recognition system using discrete wavelet transform based features extraction from the gesture images and a neural network for recognition. Using vision-based system, different sign language recognition systems have been reported for Malaysian [6], Arabic [7], Japanese [8] and Korean [9] sign languages. Nandy et. al. [10] were among the first to report the recognition of Indian sign language (ISL) using vision-based systems and euclidean distance metric classifier. A Histogram of Edge Frequency (HOEF) feature has been reported to be as more efficient compared to HOG features for ISL recognition [11]. Kishore et al. [12] developed a vision based ISL recognition system using image segmentation techniques. An active contours of images have been defined for the recognition of ISL in [13]. Wavelet transform [14] and B-Spline approximation [15] based methods have been developed for ISL recognition.

The numbers of work reported on glove-based sign language recognition is not as large as vision-based systems; and even fewer for ISL recognition. Digital Entry Data Glove designed by Grimes was the first glove used for understanding sign language [16]. It used sensors mounted on the glove for measuring hand movements. Data Glove developed by Zimmerman used thin flexible plastic tubes and light sources with detectors to record joint angles [17]. The Power Glove commercialized by Mattel Intellivision for controlling video game console used resistive ink printed flexible plastic bends [18]. This was followed by the development of Cyber Glove at Stanford University, and commercialized by Virtual Technologies Inc. It was equipped with 18 or 22 piezo-resistive sensors [19]. 5DT Data Glove commercialized by Fifth Dimension Technologies uses optical-fiber flexor sensors [20]. Recently developed Strin Glove was commercialized by Teiken Limited, Japan uses twenty-four inductcoders to record joint angles [21, 22]. Although these gloves have been in application for recognition of sign languages, the gloves are based on optical principle and subjected to the ambient light conditions. Further, the gloves with flexible sensors could measure the overall bending of the fingers instead of the angles at the joints. These lead to poor performance of the data gloves (except 5DT and Cyber glove) for recognition of sign languages.

In this paper, a methodology for recognition of ISL, ASL alphabets and numbers using an indigenously developed data glove, based on finger kinematics assessment, is proposed. The glove is customized with angle sensors at the finger joints and wrist. A radial basis function (RBF) kernel support vector machine (SVM) with 10-fold cross validation was used for recognition. An average recognition rate of 96.7% was achieved. Using a label matching and speech data base, recognized alphabets and numbers were translated into corresponding speech. The proposed method is novel being free from the ambient light condition unlike the other vision based techniques or light dependent measuring gloves. Further, the glove can measure the finger joint kinematics more accurately compared to the measurement of an overall bending like in resistance sensing based data gloves. The proposed methodology being the only one of its kind for recognition of ISL holds promise for development of a hand held ISL to speech translation device.

2. Methodology

Fig. 1 shows the methodology followed for recognition of sign language alphabets and numbers, and their translation into speech.

The finger and wrist joint angle information acquired through the data glove were transmitted to the pre-processing unit using frequency shift keying (FSK) modulation at 2.4 GHz. In the pre-processing unit, the data glove sensor output were converted into corresponding joint angles and a moving average filter of window size 5 samples was applied. Using the filtered data from the angle sensors, the metacarpophalangeal (MCP), proximal interphalangeal (PIP) of the fingers and wrist joint were obtained. The distal interphalangeal (DIP) joint angles were obtained from the MCP and PIP joint angles using the finger dynamic constraints [23]. These produce a joint angle feature matrix of size 1×21. This feature matrix is normalized through standardized feature scaling to remove the individual subjectivity. This normalized feature matrix was fed to a RBF kernel SVM. The recognition result was cross validated through a 10-fold cross validation. The recognized sign language for the alphabets and numbers were translated into corresponding speech using a label matching technique [24].

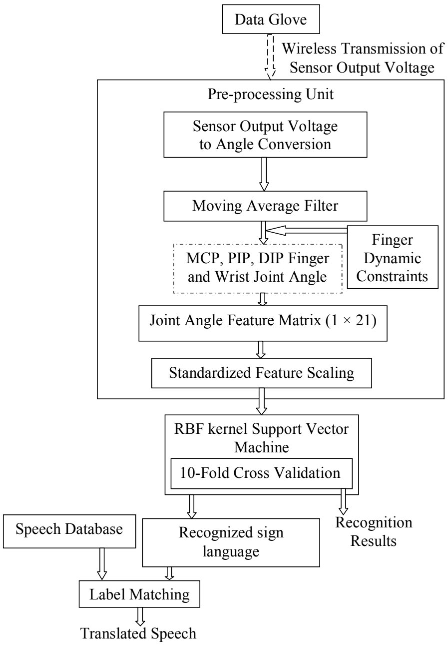

Fig. 1. Proposed Methodology for the sign language recognition and translation into speech

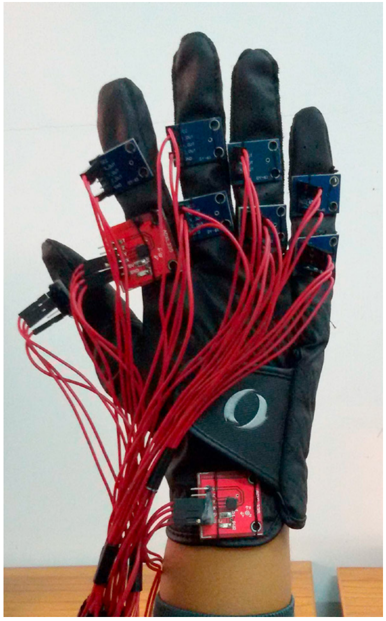

Fig. 2. Indigenously developed Data Glove

2.1. Data glove

The sign language recognition and translation into speech was accomplished using an indigenously developed data glove. The human hand is a complex anatomical structure with five digits: four fingers and one thumb. Each finger constitute of three interlinking segments: proximal, intermediate and distal phalanges. Thumb is made up of only proximal and distal phalanges. The joints on the finger are named: DIP, PIP, MCP joints [25]. Inspired by the anatomy of human hand joint positions, a leather glove is customized with ten angle sensors at the MCP, PIP and wrist joints. The functional units of the glove are:

- Accelerometer ADXL335, an analog accelerometer used as the finger joint angle sensor. These angle sensors work based on the capacitive sensing principle [26]. For a particular hand gesture during the sign language alphabets and numbers, the sensors give voltage values as output corresponding to the joint orientation.
- Controller Unit consists of an ATmega 2560 AVR microcontroller and acts as the interface between the glove sensors and the wireless transmission unit. The angle sensors' data are directly fed to this controller wherein analog values are converted into digital and fed to the transmission unit.
- FSK transceiver module was used for data transmission between the glove and the sign language recognition unit. It works at 2.4 GHz frequency in half duplex mode. The digital values corresponding to the sensor outputs transmitted from the transmitter were received by its receiver section and fed to the recognition and translation unit.
- Recognition and Translation Unit was used for sign language recognition using a RBF-kernel SVM. The translation of the recognized sign language into speech was achieved through a label matching technique.

Fig. 2 shows the indigenously developed data glove.

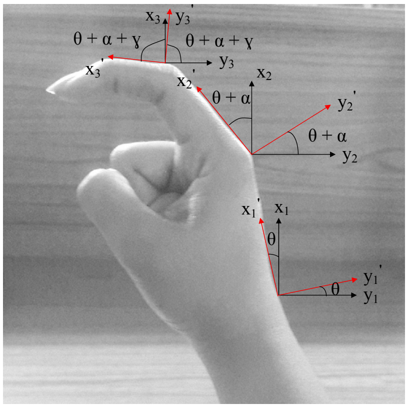

Fig. 3. Schematic of the Hand Coordinate System for Kinematic Assessment

2.1.1. Hand Kinematics Measurement

A kinematic model of human hand with the fixed frame attached to wrist and movable frames to the other joints is shown in Fig. 3. It consists of 21 Degrees of Freedom (DoF). Each finger have four DoFs: two for MCP joint flexion-extension/ abduction-adduction and one each for PIP and DIP joint flexion-extension. The thumb has three DoFs: two for MCP joint flexion-extension/ abduction-adduction and one for inter phalangeal (IP) joint flexion-extension. The wrist has two DoFs for flexion-extension/ abduction-adduction. The joint angle at a particular joint can be acquired by taking the difference of the tilt angles. The direct kinematics is applied at the MCP and PIP joint of the fingers. The joint angle at MCP was determined as:

$$\theta_{MCP} = \theta_{MCPtilt} - \theta_{wrist} \tag{1}$$

With reference to the Fig. 3, equation 1 is formulated for the joint angles at MCP and PIP as:

$$\alpha = (\theta + \alpha) - \theta \tag{2}$$

$$\gamma = (\theta + \alpha + \gamma) - (\theta + \alpha) \tag{3}$$

The joint angle at the DIP is obtained by employing the human hand dynamic constraints [23],

$$\theta_{DIP} = \frac{2}{3}\theta_{PIP} \tag{4}$$

2.2. Dataset

The data set for the sign language recognition was ASL alphabets (A to Z), ISL alphabets (C, I, J, L, O, U, Y, W) and numbers (0 to 9). The data set was constrained to limited numbers of ISL alphabets as the other alphabets use both the hands and our experimental set up is limited with a single data glove. Fig. 4 and Fig. 5 shows the ISL and ASL. Four subjects (2 male and 2 female) in the age group of 22 to 25 years took part in the experiment. Each subject, wearing the data glove, performed the sign language for the selected alphabets and numbers for 5 trials. Sign language for each alphabet and number was performed for a period of 20 secs.

2.3. Preprocessing and Feature Matrix

The sensor outputs obtained from the data glove were converted into corresponding angle following sensor specification as in [26]. The acquired angle data were subjected to low frequency noises for the hand movements during the sign language postures. A moving average filter of 5 samples window size with frequency band 5-30 Hz was applied. The windowed sensor signals corresponds to the MCP, PIP of finger and wrist joints. Using the dynamic constraints

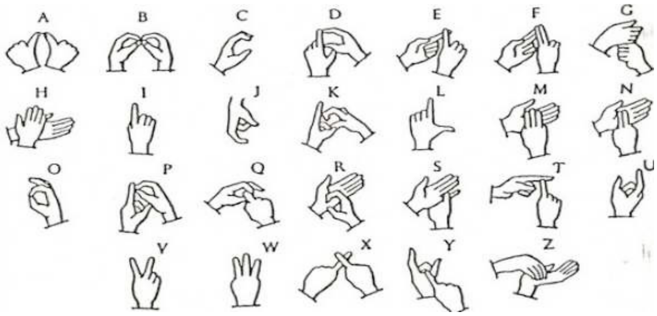

Fig. 4. Indian sign language (Adopted from [27] (Alphabets with single hand were only considered for the experiment)

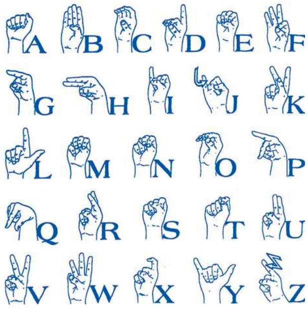

Fig. 5. American Sign Language (Adopted from [28])

for human finger as in equation 4, the DIP finger joint angles were assessed. The resulted angles were for flexion of MCP, PIP and DIP joints, adduction of MCP joints and flexion/ adduction of wrist joint. These joint angles constitute a feature matrix of size 1×21. In order to remove the dependency of the feature matrix on the subjective factors like different hand sizes, changes in hand postures for the same finger spelling, standardized feature scaling [29] was used.

2.4. Recognition and Translation into Speech

RBF kernel SVM, being robust to deal with the non-linear data [30], was used for recognition of the sign language alphabets and numbers based on the extracted feature matrix. This recognition architecture was implemented in real-time to the glove data acquisition. The best values for SVM parameters, c and γ, chosen through grid search [30], are tabulated in Table 1. A 10-fold cross-validation was done during the recognition wherein the input data set was

Table 1. Values of SVM parameters c and γ for the recognition of ISL.

Sign language	c-value	γ-value
ISL	1	0.001
ASL	1	0.003
Indian and American Numbers	1	0.001

divided into 10 subsets. Nine out of 10 equally divided subsets were used as training set and the remaining one as the testing set. This is repeated ten times using different subsets for testing in each case. The average of the ten test performance was estimated as the performance of the classifier [31]. To facilitate the translation of the recognized sign language to speech, a speech database in .mat format was created for the considered sign languages alphabets and numbers. Each speech database was annotated with labels using Speech Assessment Methods Phonetic Alphabet (SAMPA) labels [24]. On matching labels of the recognized sign language alphabets or numbers with the labels of the speech in the database, corresponding speech file was executed translating the sign language into speech.

3. Experimental Results

3.1. Hand Kinematics Measurements

Following the finger kinematics approach as detailed in section 2.1.1, finger joint angles were obtained using the data glove. A standard set of joint angle measurements for the sign language alphabets and numbers under study was recorded using a stainless steel rotary type goniometer. The joint angles obtained using the data glove were compared to the goniometer recordings for finding the accuracy of angle measurement in terms of standard deviation. The glove could measure the finger joint angles with an accuracy±standard deviation for MCP±2.14°, PIP±1.73° and DIP±1.49° during flexion/ extension and abduction/ adduction movements involved in sign language alphabets and numbers. Table 2 shows the accuracy of the data glove measurements for ISL, ASL and numbers.

Table 2. Accuracy and Standard Deviation of Joint Angles in degree measured by the Data Glove for ISL, ASL and Sign Numbers

	MCP joint	PIP joint	DIP joint
ISL	MCP±2.34°	PIP±1.57°	DIP±1.77°
ASL	MCP±1.67°	PIP±2.04°	DIP±1.36°
Sign Numbers	MCP±2.43°	PIP±1.58°	DIP±1.36°

3.2. Recognition of Sign Language Alphabets and Numbers

The performance of the proposed methodology was evaluated with recognition rates for ISL, ASL alphabets and sign numbers. It was evaluated with the feature normalization as well as without feature normalization. Confusion matrices in Fig. 6, Fig. 7 and Fig. 10 shows the recognition results for the ISL, sign numbers and ASL as 95%, 95% and 92% respectively, without feature normalization technique. It produced an average recognition rate of 94%.

Predicted class label \ Actual class label	1	2	3	4	5	6	7	8	Acc (%)
1	10								100
2		10							100
3			10	2					100
4				8			1		80
5					10	1			100
6						9			90
7							9		90
8								10	100
Average accuracy percentage									95

Fig. 6. Confusion matrix for ISL

Predicted class label \ Actual class label	1	2	3	4	5	6	7	8	9	10	Acc (%)
1	10										100
2		10	2								100
3			8			2					80
4				10							100
5					10		1				100
6						8					80
7							9				90
8								10			100
9									10		100
10										10	100
Average accuracy percentage											95

Fig. 7. Confusion matrix for sign numbers

The confusion matrices stating the recognition results with the feature normalization are shown in Fig. 8, Fig. 9 to Fig. 11. It produced a recognition rate of 97.5%, 97% and 95.7% for the ISL, sign numbers and ASL with an average recognition rate of 96.7%.

We summarize the recognition results in comparison to the results obtained using two other advanced data gloves in Table 3. The work by Mohandes [32] used two cyber gloves for recognition of Unified Arabic sign language and reported a recognition rate of 99%. Ramakant et al. [20] reported recognition of ASL for alphabets and numbers using 5DT glove and a camera system with an accuracy of 95%. From the work reported in this paper, it has been

Predicted class label \ Actual class label	1	2	3	4	5	6	7	8	Acc (%)
1	10								100
2		10							100
3			10						100
4				10	2				100
5					8				80
6						10			100
7							10		100
8								10	100
Average accuracy percentage									97.5

Fig. 8. Confusion matrix for ISL

Predicted class label \ Actual class label	1	2	3	4	5	6	7	8	9	10	Acc (%)
1	10										100
2		10									100
3			10								100
4				10							100
5					10						100
6						10	3				100
7							7				70
8								10			100
9									10		100
10										10	100
Average accuracy percentage											97

Fig. 9. Confusion matrix for sign numbers

Predicted class label \ Actual class label	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	Acc (%)
1	10																										100
2		10																									100
3			10																								100
4				10																							100
5					10																						100
6						10																					100
7							10		4																		100
8								10																			100
9									6																		60
10										10																	100
11											10				3												100
12												7															70
13													10														100
14														8													80
15														2	7						2		2				70
16																10											100
17																	6										60
18												3						10									100
19																			10								100
20																	4			10							100
21																					8						80
22																						10					100
23																							8				80
24																								10			100
25																									10		100
26																										10	100
Average accuracy percentage																											92.3077

Fig. 10. Confusion matrix for ASL

Predicted class label \ Actual class label	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	Acc (%)
1	10																										100
2		10																									100
3			10																								100
4				10																							100
5					10																						100
6						10																					100
7							10																				100
8								10																			100
9									10																		100
10										10																	100
11											10																100
12												10															100
13													10														100
14														8													80
15														2	10						3		2				100
16																10											100
17																	10										100
18																		10									100
19																			10								100
20																				10				4			100
21																					7						70
22																						10					100
23																							8				80
24																								6			60
25																									10		100
26																										10	100
Average accuracy percentage																											95.7692

Fig. 11. Confusion matrix for ASL

found that the proposed method achieved a comparable recognition rate for ASL, ISL alphabets and numbers using an indigenously developed data glove. It is better in terms of recognizing more number of sign languages. Further, the proposed methodology was customized with translation of recognized sign language to speech; which is an essential component for use by the community of interest.

Table 3. Comparison of the recognition results

Author	Sign Language	Recognition
Mohandes [32]	Arabic sign language	99%
Ramakant et al. [20]	ASL, Sign numbers	95%
Reported Work	ASL, ISL, Sign numbers	96.7%

4. Conclusion

We have reported a real-time recognition of ISL and ASL alphabets and numbers based on hand kinematics using an indigenously developed data glove. Finger joint angle sensor data from the glove are transmitted to the pre-processing unit using FSK at 2.4 GHz. Moving average filter was used to remove the inherent noises. Standardized feature scaling technique was applied. This is an important step for removing the subjectivity and to improve the recognition results. Average recognition rates of 96.7% was achieved for the ISL, ASL and sign numbers. The proposed methodology being based on the data glove overcomes the limitations of vision based systems. The recognized sign language was translated into speech using a label matching technique. An extension of the presented work for sentence-based sign language recognition will lead to an enterprising device; which is part of on-going research.

Acknowledgement

Financial assistance under Grant No. 394/14 IF.I is gratefully acknowledged.

References

[1] K. Assaleh, T. Shanableh, M. Fanaswala, F. Amin, H. Bajaj, Continuous Arabic Sign Language Recognition in User Dependent Mode, Journal of Intelligent Learning Systems and Applications 2 (1) (2010) 19–27.

[2] S. A. Mehdi, Y. N. Khan, Sign Language Recognition using Sensor Gloves, in: 9th International Conference on Neural Information Processing, Singapore, 2002, pp. 2204–2206.

[3] T. Starner, A. Pentland, Real-Time American Sign Language Recognition from Video Using Hidden Markov Models, in: International Symposium on Computer Vision, Florida, USA, 1995, pp. 265–270.

[4] S. Liwicki, M. Everingham, Automatic Recognition of Fingerspelled Words in British Sign Language, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, Florida, USA, 2009, pp. 52–57.

[5] A. K. Sarkaleh, F. Poorahangaryan, B. Zanj, A. Karami, A Neural Network based System for Persian Sign Language Recognition, in: IEEE International Conference on Signal and Image Processing Applications, Kuala Lumpur, Malaysia, 2009, pp. 145–149.

[6] R. Akmeliawati, M. P. L. Ooi, Y. C. Kuang, Real-Time Malaysian Sign Language Translation using Colour Segmentation and Neural Network, in: International Conference on Instrumentation and Measurement Technology, Warsaw, Poland, 2007, pp. 1–6.

[7] N. Rashid, Y. Alginahi, Real-Time Arabic Sign Language (ArSL) Recognition, in: International Conference on Communications and Information Technology, Hammamet, Tunisia, 2012, pp. 497–501.

[8] M. V. Lamar, M. S. Bhuiyan, A. Iwata, Hand Alphabet Recognition using Morphological PCA and Neural Networks, in: International Joint Conference on Neural Networks, Washington, D.C., USA, 1999, pp. 2839–2844.

[9] A. Park, S. Yun, J. Kim, S. Min, K. Jung, Real-Time Vision-based Korean Finger Spelling Recognition System, International Journal of Computer, Electrical, Automation, Control and Information Engineering 2 (8) (2008) 2623–2628.

[10] A. Nandy, S. Mondal, J. S. Prasad, P. Chakraborty, G. C. Nandi, Recognizing and Interpreting Indian Sign Language Gesture for Human Robot Interaction, in: International Conference on Computer and Communication Technology, Allahabad, India, 2010, pp. 712–717.

[11] H. Lilha, D. Shivmurthy, Evaluation of features for automated transcription of dual-handed sign language alphabets, in: International Conference on Image Information Processing, Himachal Pradesh, India, 2011, pp. 1–5.

[12] P. V. V. Kishore, P. R. Kumar, E. K. Kumar, S. R. C. Kishore, Video Audio Interface for Recognizing Gestures of Indian Sign Language, Journal of Image Processing,.

[13] P. V. V. Kishore, P. R. Kumar, A model for real time sign language recognition system, International Journal of Advanced Research in Computer Science and Software Engineering 2 (6) (2012) 29–35.

[14] P. V. V. Kishore, P. R. Kumar, A video based indian sign language recognition system (inslr) using wavelet transform and fuzzy logic, International Journal of Engineering and Technology 4 (5) (2012) 537–542.

[15] M. Geetha, U. C. Manjusha, A Vision based Recognition of Indian Sign Language Alphabets and Numerals using B-Spline Approximation, International Journal on Computer Science and Engineering 4 (3) (2012) 406–415.

[16] G. J. Grimes, Digital Data Entry Glove Interface Device, u.S. Patent 4414 537 (1983).
URL `https://www.google.com/patents/US4414537`

[17] T. G. Zimmerman, Optical Flex Sensor, U.S. Patent 4 542 291 (September 1982).
URL `http://www.google.com/patents/US4542291`

[18] P. H. Veltink, H. G. Kortier, H. M. Schepers, V. I. Sluiter, R. A. Brookhuis, T. S. J. Lammerink, R. J. Wiegerink, PowerGlove, Concepts and Current Results, in: XII International Symposium on 3D Analysis of Human Movement, Bologna, Italy, 2012, pp. 42–45.

[19] A. G. E. Mulder, S. S. Fels, Sound Sculpting: Manipulating Sound through Virtual Sculpting, in: 1998 Western Computer Graphics Symposium, 1998, pp. 15–23.

[20] Ramakant, N. K. Shaik, L. Veerapalli, Sign Language Recognition through Fusion of 5DT Data Glove and Camera based Information, in: IEEE International Advance Computing Conference, pages = 639-643, address = Bangalore, India, year = 2015.

[21] T. Kuroda, Y. Tabata, A. Goto, H. Ikuta, M. Murakami, Consumer Price Data-Glove for Sign Language Recognition, in: 5th International Conference on Disability, Virtual Reality and Associated Technologies, Oxford, UK, 2004, pp. 253–258.

[22] L. Dipietro, A. M. Sabatini, P. Dario, A Survey of Glove-Based Systems and their Applications, IEEE Transactions on Systems, Man, and Cybernetics 38 (4) (2008) 461–482.

[23] H. Rijpkema, M. Girard, Computer animation of knowledge-based human grasping, in: Proceedings of the 18th annual conference on Computer graphics and interactive techniques, Las Vegas, USA, 1991, pp. 339–348.

[24] J. Harrington, Phonetic Analysis of Speech Corpora, Wiley-Blackwell, Germany, 2010.

[25] H. Gray, Anatomy of the Human Body, Philadelphia: Lea and Febiger, Heidelberg, 1918.

[26] C. J. Fisher, Using an Accelerometer for Inclination Sensing, Tech. rep., AN-1057, Application Note, Analog Devices (2010).

[27] R. A. Tennant, M. G. Brown, The American Sign Language Starter, Gallaudet University Press, 2002.

[28] D. Deora, N. Bajaj, Indian Sign Language Recognition, in: International Conference on Emerging Technology Trends in Electronics, Communication and Networking, Gujarat, India, 2012, pp. 1–5.

[29] D. Li, B. Zhang, C. Li, A Feature-Scaling-Based k-Nearest Neighbor Algorithm for Indoor Positioning Systems, IEEE Journal on Internet of Things 3 (4) (2016) 590–597.

[30] C. W. Hsu, C. C. Chang, C. J. Lin, A Practical Guide to Support Vector Classification, Tech. rep., http://www.csie.ntu.edu.tw/ (2009).

[31] R. Kohavi, A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection, in: 14th International Joint Conference on Artificial Intelligence, USA, 1995, pp. 1137–1143.

[32] M. A. Mohandes, Recognition of Two-Handed Arabic Signs using the Cyber Glove, Arabian Journal for Science and Engineering 38 (3) (2013) 669–677.