© 2017 IJEDR | Volume 5, Issue 2 | ISSN: 2321-9939

Perlustration of Deaf-And-Dumb Alphabet Detection and interpretation

[1]Ms.N.Priyadharsini, [2]Mrs.N.Rajeswari
PG Student (ME-CSE), Assistant Professor
Department of Computer Science And Engineering, SVCE, Sriperumbudur, India

---

Abstract— **A sign language appertains to recognize the meaningful expressions which uses the gestures like combined hand-shapes, orientation and movement of the hands, arms or body, facial expressions and lip-patterns instead of sound to convey ideas. It is of uttermost importance in designing an intelligent and efficient human–computer interface. The applications of sign language ranges from medical rehabilitation to loud venues. However, successful recognition of lexical signs is not sufficient for understanding of proper Sign language communication. The Non-manual signs and the grammatical processes, results in the variation in the appearance of signs are integral aspects of interaction but have received comparatively less attention. In this survey, we examine the data acquisition, preprocessing, feature derivation and classification methods employed for scrutinize the sign language gestures. These are discussed with respect to the issues like modeling transitions between signs in continuous signing, signer independence, and adaptation, also with the overall progress towards a true test of sign recognition systems—dealing with natural signing by native signers. Every hand gesture recognition is depending on characters in different Sign Language (SL). The related research area of sign gesture recognition is Human Computer Interaction (HCI) and image processing which helps to solve this problem. Existing challenges and future research possibilities are also highlighted.**

Index Terms— **Sign language recognition** (key words)

I. INTRODUCTION

In the present day framework, computers have become a key element of our society for interaction and intelligent computing. Surfing the web, typing a letter, playing a video game, storing and retrieving data are few examples of tasks that involve the interaction of computers. Computers will increasingly influence our everyday life because of the constant decrease in the price of personal computers. The efficient use of computer applications requires more interaction. Human–computer interaction is assuming utmost importance in our daily lives. Thus, HCI has become an active and interesting field of research in the past few years [1]. To utilize this new phenomenon efficiently, many studies have examined computer applications and their requirement of increased interaction. Thus, human computer interaction (HCI) has been the frisky field of research.

Signs are very expressive, meaningful body motions involving physical changes of the body parts like fingers, hands, arms, head, face, or body with the intent of: 1) conveying the meaningful information or 2) interaction with the environment. They constitute one interesting subspace of possible human motion. A sign may also be recognized by the environment as a compression technique for the information to be transmitted elsewhere and subsequently reconstructed by the receiver. Sign recognition has wide-ranging applications [2] such as the following:

- developing aids for hearing impaired people;
- enabling young children to interact with computers;
- designing techniques for finding forensics;
- recognizing the sign language;
- medically monitoring patients' stress levels or emotional states;
- navigating and/or manipulating in virtual environments;
- communicating in the video conferencing;
- tele-teaching assistance/ distance learning;

Generally, there exist many-to-one mappings from concepts to signs and vice versa. Hence, gestures are incompletely specified. For example, to indicate a alphabetical letter "A" one can use signs such as a raised hand with closed palm in american sign language, or, combined thumb opened representation of both the hands in Indian sign language. Similar to the voice and manuscriptions, signs also vary between individuals, and even for the same individual between different instances. There have been varied approaches to handle gesture recognition [3], ranging from mathematical models based on hidden Markov chains [4] to tools or approaches based on soft computing [5].

II. SIGN LANGUAGES

Based on WHO, it is reported that about 5% of world population consists of the deaf mute and hard hearing people. They used some kind of hand, head, and body gesture to exchange their feelings/ideas. So almost all the nations have their own Sign Language. The sign language development is not unique for each country or sub-continent.

Table-1. Major sign languages.

S. No.	Country/ sub-continent	Sign Language	Abbn.	No. of papers Included
1	United Kingdom	The British Sign Language	BSL	1
2	United States of America	The American Sign Language	ASL	2
3	Commonwealth of Australia	The Australian Sign Language	Auslan	2
4	Japan	The Japanese Sign Language	JSL	1
5	People's Republic of China	The Chinese Sign Language	CSL	2
6	Taiwan	The Taiwanese Sign Language	TSL	1
7	Republic of India	The Indian Sign Language	ISL	2

The Table-1 represents the sign languages of influencing sub-continent/countries. The Table-1 indicates the most dominating research is going on ASL. The reason is that a large number of standard database for ASL are available and can be accessed publicly. American Sign Language is a complete, complex language thai is made of signs with the hand and other movements, which include facial expressions and postures of the body. It is the first language of many deaf people in North America, and is considered as the dominant sign language of the deaf community in the united states, in the english-speaking parts of canada, and in the parts of Mexico. ASL is the most commonly used language in U.S. The developing countries are currently focuses on the research in this field.

III. IMAGE DATABASE

Dataset is made of 100 sentences of our formal language with an average length of ten words. The longest sentence is composed of 28 words, and the shortest is of two words long[6].Nine popular gestures *Static Gesture and* Additional tests were performed to recognize different dynamic gestures[7]. The system was designed to recognize 24 American sign language hand signs[8]. dataset is included in the UCI Machine Learning repository, 2;565 samples, with 27 samples per sign[9]. multiple target objects (the face and hands) throughout an image sequence and extracts features for the recognition of sign phrases[10]. 16 Japanese sign language words and 3 Japanese finger alphabets in dual hand arm system[11]. The dataset used in this study included 200 representative CSL common sentences constituted by 181 frequently used CSL words, from which a vocabulary of 120 sub-words[12]. 10 people performed 22 hand body language gestures[13]. The database contains 11 home-service-related Taiwan sign language words and each word is performed ten times, five males and five females are invited to perform such words[14]. The database used for implementation has been self-created and includes total 130,000 videos; out of which 72,000 videos were used to create the system database and remaining 58,000 videos have been tested for checking the performance of the system[15]. dataset that comprises of a set of 20 images each for every signed alphabet of that The dataset constitutes of 520 images for the training segment and 260 images for testing[16].

IV. FEATURES USED FOR SIGN LANGUAGE RECOGNITION

An important problem while designing the sign language recognition system is the extraction of suitable distinct features that efficiently characterize the variations in signs. Since the pattern recognition techniques are rarely independent of the problem domain, it is believed that a proper choosing of the features significantly affects the performance of classification.

Three issues must be considered in feature extraction. The first issue is analyzing the region used for feature extraction. While some authors follow the ordinary framework of dividing the images into small intervals, called pixels, from each which a local feature vector is extracted, other researchers prefer to extract global statics from the whole speech utterance. Another important question is what are the best feature types for this task. Finally, what is the effect of ordinary image processing such as noise removal on the overall performance of the classifier?

V. SIGN RECOGNITION

In this section a survey of most recent works in Sign Language Recognition and their results are discussed. Hidden Markov Models (HMMs), Accelerometer and SEMG, Field Programmable Gate Arrays(FPGA) and Self Organizing Map(SOM), Histograms of Oriented Gradients(HOG) and Scale Invariant Feature Transform(SIFT), Bag Of Features(BOF),Block Search Scheme and K-curvature algorithm, Labeled Graph SVM(LGSVM) and Labeled Graph Logistic Regressor(LGLR) are the most preferred methods used for Sign Language Recognition. Sign Language Recognition based on Hidden Markov Model is presented in[14]. Recognition system for understanding the words of home-service-related sign language. Data received from sensor are sequential HMM that has been successfully applied to the speech signals, entropy based *K*-means algorithm is used to evaluate the number of states in the HMM model with the help of entropy diagram. Database contains 11 home-service-related Taiwan sign language words and each word is performed ten times, five males and five females are invited to perform such words with the average recognition rate of 91.3%.

The Accelerometer and Surface Electromyographic sensor (SEMG) is presented in [12], especially for large-vocabulary SLR systems. Data segmentation, is an important preprocessing operation, is performed to divide a continuous sign language sentence into sub-word segments. data segmentation approach is described as 1. Divide the eight-channel sEMG signals into time-shifting chunks. 2. For each windowed data chunk, calculate the average of the four sEMG channels (Ch1–Ch4) from the right arm and calculate the corresponding average energy. 3. Compare the time series with a predefined threshold , and detect the boundaries of each subword segment by defining each subword segment as a number of consecutive data chunks 4. Based on the earlier detected boundaries, enforce the same boundaries on the left sEMG channels and the ACC signals of both hands. 5. calculate the average of the four left sEMG channels (Ch5–Ch8) for each sub word and calculate its overall average energy. 6. Compare the left sEMG average energy with a threshold to determine whether the subword is two-handed or not. Sub-words can be recognized by fusing the likelihoods at the component level . The classification accuracy of 96.5% for a vocabulary of 120 signs and 86.7% for 200 sentences. In [8] a hybrid network contains self-organizing map (SOM) and Hebbian network, a single-layer feed forward neural network. Feature vectors are extracted from the input postures, then mapped to a lower dimensional map of neurons in the SOM. In addition, neuron culling is proposed to improve performance. The system was designed to recognize 24 American sign language and is achieved an accuracy of 97.1%.

To deal with the static images HOG and SIFT are presented[16]. Indian Sign Language(ISL) alphabet are both single-handed and double-handed. Hence, to make recognition easier the model first categorizes them as singlehanded or double-handed. For both categories two kinds of features, namely HOG and SIFT, are extracted. Features are extracted for a set of training images and are combined in a single matrix. After which, features for the input test image are combined with the feature matrices of the training set. Correlation is computed for these matrices and is fed to a K-Nearest Neighbor Classifier to obtain the resultant classification of the test image. Detecting dynamic sign language recognition (DSLR) system for smart home interactive applications is proposed in[6]. Comprised two main subsystems: an image processing (IP) module, enables us to recognize the individual words which use bag-of-features (BOFs) and a stochastic linear formal grammar (SLFG) module, analyzes the sentences of the sign language and determines whether or not they are syntactically valid. SLR based on signals from specialized glove is proposed in[13]. Effective recognition of gestures of hand body language, based on data from a specialized glove equipped with ten sensors. 10 people performed 22 hand body language gestures. Each of the gestures was executed 10 times, three machine learning algorithms were designed based on the classifiers 1.probabilistic neural network 2.support vector machine and 3.k-nearest neighbors algorithm.

Table 2: Performance comparison of various classifiers

S. No	Classifier	Language	Average Recognition Accuracy
1	Hidden Markov Model (HMM)	TSL	91.3%
2	Linear Discriminant Classifier(LDC)	CSL	96.5%
3	Kernel-based classifier	AuSL	98.70%
4	Support Vector Machine(SVM)	BSL	98.65%
5	Nearest Neighbour Classifier	ISL	97.5%
6	Hidden Markov Model (HMM)	ASL	92.4%
7	SOM–Hebb classifier	ASL	97.1%
8	K-Nearest Neighbor Classifier	ISL	91.2%
9	Probabilistic Neural Network, Support Vector Machine, and k-nearest neighbors	CSL	98.24%

In [7], the tracking and recognizing the real time hand gestures based on depth data collected by a Kinect sensor. A novel algorithm is proposed to improve the scanning time in order to identify the first pixel on the hand contour within this space. The k-curvature algorithm is then employed to locate the fingertips over the contour. An average recognition rate of 92.4% is achieved over 55 static and dynamic gestures. Sign Recognition based on Automatic behavior analysis Labeled Graph Support Vector Machine (LGSVM) and a Labeled Graph Logistic Regressor (LGLR) which discriminate between actions. Two major problems are of interest when analyzing behavior. First of all, we wish to automatically categorize the observed images into a discrete set of classes (i.e., classification). Second, we wish to understand the relevance of each behavioral feature in achieving this classification (i.e., decoding) algorithms allow us to achieve higher accuracy results than those of state-of-the-art algorithms in a fraction of the time.

VI. FURTHER APPLICATIONS

Some surgical procedures (like oral surgery) impede a person’s ability to talk during recovery. With SL, people can communicate without trying to talk. In Loud Venues such as rock concert or construction site, where too much background noise to have a normal conversation with the people you are with. Using SL, you can easily converse even from a distance regardless of how much background noise. The communication between vehicles at a distance while cold or raining outside need not want to roll down the windows. In the Music Industry, for people who play live music on a regular basis, SL is an imperative skill if they want to keep their hearing. Important for people who play loud amplified music or loud instruments.

With SL, it is possible to wear ear plugs and communicate.In Radio Station sound room with several people participating in a live talk show. With SL it is easy to communicate with people during a live recording without talking and interrupting the show. In secret Military Operations, special ops assignment and need to maintain complete silence (including radio silence), the SL facilitates the communication. The Under Water while scuba diving with friends, SL is used. Applicable in Library zone can discuss about project without making a noise.The Hospital Visitor while visiting someone in the hospital. The person has just fallen asleep,SL can be used.

VII. CONCLUSION

In this paper, a survey of current research work in sign language recognition system has been given. Three important issues have been studied: the features used to characterize different signs, the classification techniques used in previous research, and the important design criteria of sign language databases. There are several conclusions that can be drawn from this study.

The first one is that while high classification accuracies have been obtained for classification between different signs, The average classification accuracy of speaker-independent speech emotion recognition systems is less than 95% in most of the proposed techniques. In some cases, it is as low as 91%. For speaker-dependent classification, the recognition accuracy exceeded 95% in several studies.

REFERENCES

[1] Just, A.: Two-handed gestures for human–computer interaction. PhD Thesis (2006).
[2] C. L. Lisetti and D. J. Schiano, "Automatic classification of single facial images," Pragmatics Cogn., vol. 8, pp. 185–235, 2000.
[3] V. I. Pavlovic, R. Sharma, and T. S. Huang, "Visual interpretation of hand gestures for human computer interaction," IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 677–695, Jul. 1997.
[4] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," Proc. IEEE, vol. 77, no. 2, pp. 257–285, Feb. 1989.
[5] S. Mitra and T. Acharya, Data Mining: Multimedia, Soft Computing, and Bioinformatics. New York: Wiley, 2003.
[6] M. R. Abid, E. M. Petriu and E. Amjadian, "Dynamic Sign Language Recognition for Smart Home Interactive Application Using Stochastic Linear Formal Grammar," in *IEEE Transactions on Instrumentation and Measurement*, vol. 64, no. 3, pp. 596-605, March 2015.
[7] G. Plouffe and A. M. Cretu, "Static and Dynamic Hand Gesture Recognition in Depth Data Using Dynamic Time Warping," in *IEEE Transactions on Instrumentation and Measurement*, vol. 65, no. 2, pp. 305-316, Feb. 2016.
[8] H. Hikawa and K. Kaida, "Novel FPGA Implementation of Hand Sign Recognition System With SOM–Hebb Classifier," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 1, pp. 153-166, Jan. 2015.
[9] R. Zhao and A. M. Martinez, "Labeled Graph Kernel for Behavior Analysis," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 8, pp. 1640-1650, Aug. 1 2016.
[10] Australian sign language recognition.
[11] H. Sugiuchi, T. Morino and M. Terauchi, "Execution and description of dexterous hand task by using multi-finger dual robot hand system - realization of Japanese sign language," *Proceedings of the IEEE Internatinal Symposium on Intelligent Control*, 2002, pp. 544-548.
[12] Y. Li, X. Chen, X. Zhang, K. Wang and Z. J. Wang, "A Sign-Component-Based Framework for Chinese Sign Language Recognition Using Accelerometer and sEMG Data," in *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 10, pp. 2695-2704, Oct. 2012.
[13] P. Pławiak, T. Sośnicki, M. Niedźwiecki, Z. Tabor and K. Rzecki, "Hand Body Language Gesture Recognition Based on Signals From Specialized Glove and Machine Learning Algorithms," in *IEEE Transactions on Industrial Informatics*, vol. 12, no. 3, pp. 1104-1113, June 2016.
[14] T. H. S. Li, M. C. Kao and P. H. Kuo, "Recognition System for Home-Service-Related Sign Language Using Entropy-Based K-Means Algorithm and ABC-Based HMM," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 1, pp. 150-162, Jan. 2016.
[15] P. C. Badhe and V. Kulkarni, "Indian sign language translator using gesture recognition algorithm," *2015 IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS)*, Bhubaneswar, 2015, pp. 195-200.
[16] B. Gupta, P. Shukla and A. Mittal, "K-nearest correlated neighbor classification for Indian sign language gesture recognition using feature fusion," *2016 International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, 2016, pp. 1-5.
[17] J. Wu, L. Sun and R. Jafari, "A Wearable System for Recognizing American Sign Language in Real-Time Using IMU and Surface EMG Sensors," in *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 5, pp. 1281-1290, Sept. 2016.