Sign Language Recognition: An Overview

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Abstract- *Sign Languages have originated and evolved independently at different parts of the world. The various methods employed in sign language recognition on a global scale are reviewed in this paper. Purpose of this survey is to examine data acquisition, feature extraction and classification methods employed for sign language recognition. Due to the interconnection of these areas, vast literature is available for review. Hence the domain for literature survey is restricted to sign language research – specifically Indian Sign language.*

Keywords- Gesture Recognition System, Sign Language Recognition, Indian Sign Language Recognition

I. INTRODUCTION

Advances in image processing and pattern recognition have influenced considerably the process of sign language recognition. It is important to have an automated sign language recognizer that can reduce the gap between common people and hard to hear, so that they can be brought into the main stream. Secondly, automated sign language recognizer would provide tutoring platform without a trained interpreter who are not widely available. Lastly, the knowledge gap between common people and hard to hear people will be minimum and both can contribute to the development of the society.

Many works have been carried out in different sign languages around the world**.** Table 1 lists some of the well-known sign languages where active research works are being carried out. These sign languages have their own style or pattern of representation. So it is very clear that the problems associated with recognition differ across sign languages.

Among gesture categories, sign language is often regarded as the most structured one. Each Sign language in the world is a combination of manual and non-manual gestures with its own grammar. Category of gestures used in sign language is depicted in figure 1. In order to build a suitable automated sign language recognition system, a detailed interpretation of gestures is necessary. Due to the intrinsic differences existing across the sign languages, the approaches for their interpretation also differ.

Sign language recognition is not a simple task like speech recognition. The developments in sign language recognition are far behind speech recognition in terms of accuracy and correctness. Multiple channels are involved in sign language recognition contrary to audio channel recognition that is one-dimensional and simple.

Table 1: Popular Sign languages used around the world.

Sl.No	Country/Continent	Sign Language	Abbreviation
1	United States of America	American Sign language	ASL
2	United Kingdom	British Sign Language	BSL
3	Australia	Australian Sign Language	Auslan
4	Middle-East	Arabic Sign Language	ArSL
5	China	Chinese Sign language	CSL
6	Japan	Japanese Sign Language	JSL
7	Taiwan	Taiwanese Sign Language	TSL

The rest of the paper is organized as follows. The state of art in the recognition of sign languages like ASL, ArSL and CSL is presented in detail in section 2. The performance evaluation of various gesture recognition schemes across multiple languages is discussed in section 3. Furthermore, the progress made in ISL recognition in comparison to other languages is given in Section 4.

II. STATE OF THE ART IN SIGN LANGUAGE RECOGNITION

A survey on common methods using in gesture recognition is published in [1,2]. A detailed analysis on the recognition methods for various sign languages is reported by [3]. Figure 2 describes the general framework of a gesture recognition system.

Acquisition of image, feature extraction and its classification are the primary phases of gesture recognition. The raw image frames are pre-processed prior to analysis. Identifying the target image area is an important aspect of any recognition system. Identifying and extracting the most relevant features of a gesture plays an important role in increasing the accuracy of recognition systems. Vision based approach or direct measure approach is used in image acquisition. Data acquisition devices like Accelegloves are used in direct measure approach [4] or wearable computing approaches. However, vision based methods use skin color or textural changes to track hand gestures [5]. Colored gloves could also be used to track hands [6] (Fig:3).

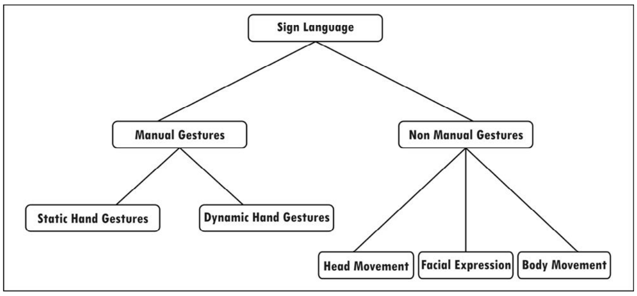

Figure 1: Category of gesture in sign language

Sign language includes both manual and non-manual gestures as shown in Fig 1. All hand gestures are considered as manual gestures while facial expression, body movement and head movement are non-manual gestures. Since dynamic gestures follow a trajectory motion, the shape of hand and motion are to be considered .But static manual gestures are based on fixed hand postures. Sign language is a continuous gesture stream that is performed one after the other to ensure meaningful communication.


Figure 3:Color glove and sensor glove

III. AN ANALYSIS OF METHODS EMPLOYED IN SIGN LANGUAGE RECOGNITION

Sign language communication is highly complex, and it has significant commonality with research in machine learning. Hand shape, location and motion trajectory of the hand and facial expressions are some of the main aspects relevant to machine analysis.

A. American Sign Language Recognition

Liang etal. [21] in 1995 made an initial attempt to develop a gesture recognition system for hearing impaired considering the wide use of ASL. The work focused on the recognition of a continuous flow of alphabets in ASL to spell a word. Sensor glove was used for capturing the gestures. Template matching recognition strategy was adopted for classification.

Gupta, Lalit et al[16] in 2001,have worked on a set of static hand gesture representing ASL signs. Features of the gesture were extracted based on the contour of the gesture. Classification was based on similarity measure.

Isaacs et al. [18] in 2004 focused on a gesture recognition system that utilized wavelet based feature vector for the recognition of 24 static ASL alphabets using still images. The pre-processing of images as well as mother wavelet for feature vector composition were optimized using Genetic Algorithms. Classification process was done using ANN classifier.

Oz, Cemil et al.[10] in 2007, presented an ASL word recognition system using Artificial Neural Networks (ANN) which converted ASL words to text. Sixty words were considered for this purpose. This system used sensory glove and 3D motion tracker to extract the features. Hand shape was defined based on joint angle between fingers, and the movement trajectory data was extracted by tracker. Signs were defined by hand shape, location, orientation, movement and distance. An accuracy rate of 95% was achieved by this approach.

Derpanis, Konstantinos G et al [26] in 2008 presented a paper to represent and recognize the hand movements that are used in single handed ASL. The approach followed was by decomposing the dynamic gestures into their static and dynamic components. Kinematic features were extracted from apparent motion used for identification for 14 primitive movements in ASL. This approach was evaluated on a database of 592 gesture sequences and yielded an overall recognition rate of 86%.

Ding, L et al. [12] in 2009, interpreted manual signs using hand shape, motion and place of articulation. Hand shape was represented as a set of affine equations. 3D motion path of the hand was tracked by the hand pose differences from the consecutive frames. The translation and rotation were estimated by using three point perspectives pose made by the object and the points were collected from camera coordinate system. Hand position was estimated by setting face as a reference. Classification was done using tree structure instead of HMM. The database includedof 576 video sequences. Class of the sign was identifiedby integrating the three hand features.

Elmezain, Mahmoud et al. [13] in 2009, recognized ASL alphabet and Arabic numbers represented by single hand motion trajectory using HMM. System used combined feature of location, orientation and velocity. There were 720 video samples and 360 video sequences for training and for testing, respectively. Proposed system gained a recognition rate of 98.33%.

Alonetal.[7] in 2009developed an ASL sign retrieval system to extract signs from a video sequence. They generated a frame work for simultaneously performing spatial segmentation, temporal segmentation and recognition. The method was first applied to a hand motion in air to represent numbers. Hand motion tracking was done using frame difference method. Learning the observation density functions was done usinga variant of the Baum-Welch algorithm. This method achieved 85 % correct detection rate.

Athitsos et al. [2009] presented a database based approach for addressing ASL recognition [8]. Two gesture problem handled in this were hand shape and hand motion recognition. The hand motion has to be discriminated between the signs. Dynamic time wrapping distance measure was used in this analysis. Performance was evaluated using three measures: retrieval time, K-percentile accuracy and classification accuracy with 33 %.

Rashid et al. [23] in 2009 described an approach for hand posture recognition for static alphabets and numbers used in ASL. Segmentation of bare hand was exploited using normal Gaussian distribution information. Statistical and geometrical properties of the hand were treated as feature vectors. Hu moment invariant was considered for statistical feature vector generation. In order to avoid misclassifications in alphabets, curvature analysis was also carried out.SVM classifier was used for classification and recognition. Proposed frame work gained an accuracy rate of 98.65% for ASL alphabet and 98.6% for numerals. The same authors tried another experiment using Microsoft Kinect sensor for capturing hand gestures [24]. Feature extraction was based on the depth and intensity of the image captured. Deep Belief Network was used for classification and recognition.

Kong et al. [17] in 2010 presented an approach to segment phonemes from ASL sentences. Hand motion trajectories of the signed sentences were segmented using rule base algorithm. Principal Component Analysis as feature descriptor was used to represent the segments. Training was done using Hidden Markov Model to recognize the sequence of the phonemes in the sentences. The average recognition error was 11.4%.

Ullahetet al. [14] in 2011 presented a research work based on Cartesian Genetic Programming (CGP) for learning ASL alphabet recognition system using. The average recognition accuracy was greater than 90%. .

Kim,Taehwan et al. [19] in 2012 presented a system for recognition of finger spelling sequences in ASL from video. Each signer has finger spelled words from a list of 300 words. Sixty image frames were taken from the video. System followed skin color based hand segmentation. Feature extraction of the segmented hand was generated using SIFT. PCA was applied on the feature vector for dimension reduction. Dimensionally reduced feature vector was taken by multilayer perception with one hidden layer having 1000 hidden nodes. Outputs of MLP were used as observations in HMM based recognizer.

Kurakin, Alexey et al. [20] in 2012presented a paper on the recognition ofdynamic hand gesture in ASL. Feature vector included of velocity of hand centre, rotation parameter of hand and shape descriptor. This study calculated the cell occupancy feature and silhouette feature from uniformly gridded hand image and applied PCA for feature dimension reduction. Training and testing was done using HMM.

Nguyen, Tan Dat et al. [25]in 2012 presented a paper for tracking and recognizing facial features exhibiting facial expressions used in ASL. This paper handled both head pose change and facial expression change in depicting a sign. Probabilistic Principal Component Analysis (PPCA) was used as shape vectors to learn the subspace transition probabilities for the tacking algorithm. Recognition framework was analyzed using nine HMMs and an SVM classifier and the study yielded an accuracy of 91.76%.

Bhat, Nagaraj N et al.[9]in 2013, proposed a method for static hand gesture recognition using radial enclosing of edge image and Self Organizing Map (SOM). Eighteen hand gestures were considered for this approach and this method had attained 92% recognition rate.

Tangsuksantet al[15] in 2014 used static hand postures representing ASL alphabets for sign recognition. This research designed a glove with six different color markers and developed algorithm for alphabet classification. The study used two camera to extract 3D coordinate points from each color marker to act as feature of the sign. Features were classified using feed forward Artificial Neural Network and yielded an accuracy of 95%.

Liu, Jingjing etal.[22] in 2014proposed an automatic recognition system for non-manual grammatical markers based on head pose and facial expressions used in ASL.This paper analysed eyebrow raising and lowering, and different types of head movements such as head nods and shakes. Features are based on facial geometry and appearance along with head pose obtained through 3D deformable face tracker based on adaptive ensemble of Active Shape Models (ASM). Non manual event recognition was employed using two levels of CRF. Precision, recall and F1score values were more than 80%.

B. Arabic Sign Language Recognition

Shanableh et al. [40]in 2007 proposed feature extraction based on spatio-temporal feature of the ArSL gesture using 2-D Discrete Cosine Transform. HMM was used to classify images based on the temporal dependencies.

Shanableh et al. [31] in 2007 presented a variety of feature extraction methods for recognition of ArSL. Purpose of the system was to extract the sign representing images from the video stream and identify the extracted sign.The identified image was then transformed into the frequency domain and parameterized into a precise and concise feature sets. Classification was done using HMM and comparison was done using KNN and Bayesian classifiers.

Al-Rousan et al. [30] in 2009 introduced an ArSL recognition system based on HMM model. Thirty isolated words were used for this purpose. Feature extraction was done using Discrete Cosine Transform (DCT).This work achieved a recognition rate ranging from 90.6% to 98.13%.

Tolba, M. F etal. [32]in 2010 proposed a system to identify hand poses represented in a sentence of three words. The data set consisted of 30 sentences using 100 words. Feature extraction was done using pulse-coupled neural network (PCNN). Sign recognition was done using ‘‘graph-matching’’ algorithm. More than 70% recognition rate was achieved by this method.

Mohandes et al. [36] in 2013 presented a paper for two handed sign system using glove data. Features extracted from glove data and hands tracking based on decision level using Dempster Shafer theory were combined to represent the feature vector. The combined feature descriptor gained 98.1% accuracy rate for the recognition system.

Elons, A. S [33] in 2014 described a recognition system to identify six facial expressions used in ArSL. Feature extraction was done using Recursive Principle Components (RPCA). Multilayer Perceptron (MLP) was used for classification,. They also integrated facial expression with hand gestures and achieved 88% to 98% accuracy.

Mohandes et al. [34,35] in 2014 developed a system for Arabic alphabet sign recognition using Leap Motion Controller (LMC).Twenty eight Arabic alphabet signs with ten samples of each were collected from a single signer.Twelve features were extracted out of 23 values given by the LMC to represent each frame. Classification was done using Nave Bayes Classifier. NBC gave an accuracy rate of 98.3%.

Tubaiz et al. [29], in 2014 proposed a system having dataset of 40 sentences using 80 words. Two DG5-Vhand data gloves were used to capture the hand gestures.Camera setup was used to synchronize hand gestures with their corresponding words. K-NN classifier was used for testing.

Al-Jarrah et al. [27] in 2015 proposed a recognition system for ArSL alphabets. Two feature extraction schemes namely boundary features and region features were computed and used for the representation of hand gesture. Boundary features were extracted as the length of line segments originating from the centroid of the hand gesture. Region features, were extracted after segmenting the hand gesture region into five clusters using k-means clustering technique. Adaptive Neuro-Fuzzy Inference System(ANFIS) model was used for training and testing and a recognition rate of 97.5 % was achieved on using 10 rules.

Tharwat, Alaa et al.[28] in 2015 used SIFT feature descriptors for representing static ArSL gestures. Linear Discriminant Analysis (LDA) was used for dimensionality reduction. Classifiers like SVM and K-NN were used for testing and this method achieved 99% recognition rate.

Aujeszky, Tamás et al. [37] in 2015 presented a paper using Microsoft Kinect device for gesture recognition process and attained 96% of accuracy. Aly, Salehet.al. [38] in 2014 described dynamic gestures using spatiotemporal Local Binary Pattern feature vector. Data set consisted of 23 signs and classification was done using SVM classifier. This method gained 99.5% accuracy rate. Aly, Sherin et. al. [39] in 2014 analysed the same database using LBP with PCA for dimension reduction and training by HMM model.

C. Chinese Sign Language Recognition

Fang, G.L et al. [42, 43, 44, 45, 46] proposed different methods for Chinese Sign Language recognition system. Data glove based feature extraction and classification using self-organizing feature maps (SOFMs) with HMMon a database of 208 videos is described in [43]. They achieved 1.9% improvement in the accuracy rate compared to their previous work [42], which had an accuracy rate of 91.9%.

Quan, Y et al. [47] in 2010 extracted features based on temporal and spatial characteristics of a video sequence consisting of CSL manual alphabet images. Linear SVM classifier was used for identification process and the method achieved 99.7% recognition rate for letter 'F'.

Wang, C.L et al. [48] in 2002 extracted signs from sign data streams using Dynamic Programming (DP) and used ANN approach combining k-means for classification. Seventy one hand postures were used in this analysis. In [49], raw data were collected using Cyber Glove and a 3-D tracker. HMM was used for recognition purpose and an accuracy rate of over 90% was achieved.

Zhou, Y et al. [50] in 2008 used Volume Local Binary Patterns (VLBP) as feature descriptor andPolynomial Segment Model(PSM) to represent temporal evolution of sign features as a Gaussian process with time-varying parameter. This method outperformed conventional HMM methods by 6.81% in recognition rate. Zhou, Y et al. [51] in 2007 presented a method using etyma-based signer adaption for CSL vocabulary.

A summary of the review conducted is given in Table 2 and 3.

D .Indian Sign language Recognition

So far very few studies in Indian Sign language have been documented. Table 4 illustrates the research work done in this area. Major works has been done for manual gestures. Especially in recognizing static gestures from still hand postures or spotting static gestures from continuous stream of gestures.
The graphical analysis presented in figure 4 and 5 clearly indicates the quantum of works carried out in ASL compared to other sign languages. Among the languages, lowest number of published research works was in ISL. The year wise analysis of research in ISL clearly indicates that proper emphasis for ISL was given only recently. Therefore, this emphasizes the need for more research in this area.

Sign language recognition involves simultaneous monitoring of different body articulators and their synchronization and integration by following a multimodal approach [1]. Three main channels that require focus in sign language recognition are static hand gestures where hand shape/pose represents a particular meaning, dynamic gestures consisting of hand shape and motion trajectory and facial expressions. Several complexities are associated with these channels and the performance of the recognition system depends significantly on the way in which there complexities are addressed. Therefore this work concentrates on finding decisive feature extraction methods which can help in the building of high performance ISL recognition system. The constraints that make gesture recognition complex are:

1. Static gestures with resemblances
2. Static overlaid gestures
3. Similar dynamic gestures giving different meaning depending on the hand motion trajectory.
4. Facial expression changes occurring in sign language sentences.

Selection of appropriate feature descriptors for the three main channels of sign language communication plays an important role in the recognition system. Figure 5 depict system architecture for a sign language recognition system.

Author	Sign Vocabulary	Features Extracted	Classification Methods	Accuracy	Language
Bhat, Nagaraj N., et al.[9]	ASL alphabets	Radial enclosing of egde of the image	Self-Organizing Map (SOM)	92%	ASL
Karami,et al [63]	32 static hand gestures PSL alphabets	Discrete Wavelet Transform (DWT)	Multi-Layer Perceptron (MLP)	94%	Persian Sign Language (PSL)
Teng, Xiaolong, et al, [64]	20 static hand gestures	Local Linear Embedding algorithm	Distance measure	90%	CSL
Oz, Cemil, et al, [10]	30 dynamic gestures	Sensor glove and 3D motion tracker	ANN	95%	ASL
Derpanis, K.G.,et al [11]	Dynamic gestures with 14 motions	Kinematic features	KNN with Euclidian Distance measure	86%	ASL
Ding, L.et a l[12]	Dynamic gestures	Translation and rotation by using three point perspective pose made by the hand	HMM		ASL
Elmezain, Mahmoud, et al [13]	Motion trajectory	Features based in orientation, location and velocity	HMM	98.33%	ASL
Rashid et al [23]	Static gestures	Hu moment invariant	SVM	98.6%	ASL
Al-Rousan, M et al [30]	Static Isolated words	Discrete Cosine Transform	HMM	90.6% to 98.13%	ArSL
Tolba, M. F.,et al [32]	Hand pose	Pulse coupled Neural Network	Graph matching algorithm	70%	ArSL
Tharwat, Alaa, et al.[28]	Static gestures	Scale-Invariant Feature Transform	SVM	99%	ArSL
Aujeszky, Tamás et al [37]	Dynamic Gestures, 23 signs	Local Binary Pattern	SVM	99.5%	ArSL
Wang, C.L., et al [48]	Manual alphabets	Feature extraction based on Cyber glove	ANN & Dynamic programming by combining K-mean cluster	90%	CSL

Table 2: Manual Gestures Recognition Methods on Multiple Sign Languages

IV. CONCLUSION

The literature survey enabled to identify the quantum of research work carried out in various sign languages and their success. Many research works are carried out in ASL covering different channels of sign language recognition. Research works in Arabic and Chinese sign languages are focused mainly on manual gestures. The survey also indicated the paucity of works in facial expression changes and integrating different channels of sign language recognition. Each sign language is different and therefore, independent research is required due to their inherent complexities. Therefore, this study conveys the need to conduct more research in ISL and the requirement to test feature descriptors for their potential to tackle the hidden complexities in gesture recognition

Author	Sign Vocabulary	Features Extracted	Classification Methods	Performance	Language
Liu, Jingjing, et al[22]	1.Eyebrow raising and lowering 2. Head nods and shakes	3D de face tracker based on an adaptive ensemble of formable of ASMs (Active Shape Model)	2 level Conditional Random Field (CRF)	80%	ASL
Nguyen, Tan Dat, et al [25]	Head pose change and facial expressional change in depicting sign	Probabilistic Principal Component Analysis (PPCA)	HMM and SVM	91.76%	ASL
Elons, A. S., [33]	Six facial expressions used in ArSL	Recursive Principle Components(RPCA)	Multilayer Perceptron	Range between 88% to 98%	ArSL
Hrúz, M., J, [65]	Head move, facial expression,lip move	Active Shape Model (ASM) with land mark detector(LD)	HMM	80%	General Sign Language
Von Agris,et al [66]	Facial expression and lip outline	Active Appearance Model		80.2% to 96.9%	German Sign Language

Table 3: Non_ManualGesturesRecognition Methods on Multiple Sign Languages

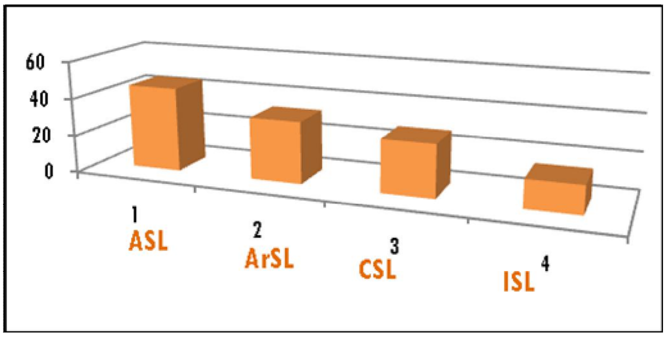

Figure 4: Volume of research done in various Sign Languages

Author, Year	Sign Vocabulary	Features Extracted	Classification Methods	Gesture Set	Performance
Nandy, Anup, et al, 2010 [52]	22 words	Direction histogram with 18 bins and 36 bins	Euclidean distance and K-nearest neighbor metrics.	Manual, Static gestures	K-nearest neighbor gives good classification with 36 bin histogram with an accuracy ranging from 61.93% to 100%
Rekha, J.et al, 2011 [53]	Alphabets	Principle Curvature based region with wavelet packet decomposition	Hand postures are classified using Support Vector Machine. Dynamic gestures are classified using Dynamic Time Warping.	Manual, Static and dynamic gestures.	Static gestures with 91.3% and dynamic gestures with 86.3%.
Kishore, P,et al , 2011 [54]	Set of words	Elliptical Fourier descriptors for shape feature extraction and principal component analysis for feature set optimization and reduction.	Fuzzy classification	Manual, Static gestures	91%
Tewari, et al, 2012, [55]	Static Alphabets	Two Dimension Discrete Cosine Transform (DCT) for each region is computed and feature vectors are formed from these DCT coefficients.	Kohonen Network	Manual, Static gestures	80%
Singha et al,2013 [57]	Static Alphabets	Eigen Vectors	Euclidian distance	Manual, Static gestures	Average recognition rate of 97%.
Geetha, M.,et al, 2012[59]	Static Alphabet	Maximum Curvature Points as key frames for gesture shape identification	Support Vector Machine	Manual, Static gestures	Accuracy > 88%
Dour, Shweta et al, 2013 [58]	Static alphabets	Centre of gesture, distance of measure to boundary and degree measure as feature measures	Fuzzy classification	Manual, Static gestures.	Accuracy >68%
Geetha, M.,et al, 2013[61]	10 words	Axis of Least Inertia is proposed for trajectory based feature extraction	Euclidian distance	Manual , Dynamic gestures	Compile time for each word is between 70 to 130 seconds.

Table 4: Indian Sign language Recognition

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