Analysis of Multiple Sign Language Recognition Using Leap Motion Sensor

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***Abstract*— Sign acquisition was mainly done using camera or sensor. Due to the invention of some advance devices like Leap Motion Sensor and Kinect the researchers have experienced new horizon for making Sign Language Recognition system more accurate. In this paper, an analysis of different Neural Networks for three sign languages is presented. Many experiments are performed for measuring the performance of NN. Sign Language recognition system is developed for three sign languages namely ASL, CSL and ISL using Leap Motion Sensor. Leap Motion sensor overcomes the major issues in real time environment like background, lightening condition, and occlusion. The leap motion sensor captures the hand gesture and gives finger position in 3D format. The positional information of five finger tips along with center of palm for both the hand is used to recognize sign posture. Signs are performed using one hand mainly and some signs in ISL are performed using both the hands. While experimentation it is observed that by keeping Leap Motion sensor little inclined, the depth information was more accurate and sign was properly visible in skeleton form. So 10 degree inclination is fixed up for sensor. So that depth information is properly extracted. The focus was mainly on Finger spell recognition so dynamic signs are not considered. 32 signs of ASL, 34 signs of CSL and 33 signs of ISL are recognized. Database is created using number of users belongs to different age, sex and region. Different Neural Network classifiers like MLP, GFF and SVM are trained and tested.**

For ASL recognition maximum classification accuracy as 90% is obtained on CV dataset using MLP NN. For CSL recognition it was 93.11% on CV dataset using SVM NN. In ISL recognition, maximum classification accuracy of 96.36% is obtained on CV dataset using GFF NN. Although Leap Motion sensor tracks both the hand accurately it can't track non manual signs which involve other body parts and facial expressions.

***Keywords*— American Sign Language (ASL), Indian Sign Language (ISL), Chinese Sign Language (CSL).**

I. Introduction

Sign language is a non verbal language used by deaf-mutes and conveyed through gestures performed by body parts which mainly includes hands and facial expressions. Hand shape, hand posture, hand location and hand motion are considered as manual parameters. While as head and body posture, facial expression, gaze and lip patterns are considered as non manual parameters. Some signs can be distinguished by manual parameters alone, while others remain ambiguous unless additional non-manual information, in particular facial expression, is made available. According to the media of sign acquisition , there are two types of sign language recognition system: system based on instrumented glove and system based on vision [1].

Sensor-based recognition systems mainly uses instrumented gloves to acquire the gesture. Sensors measure information related to the shape, orientation, movement, and location of the hand. However the Glove based system is little bit hectic as signer has to wear many sensors on wrist and arms while performing sign which may create difficulty for natural sign performer.

Vision based recognition system is mainly uses camera. Here the segmentation is color space based. So there are chances that skin color of hand, cloth, face and surrounding environment may be similar. So this creates difficulty in hand segmentation which may result in occlusion problem.

Recently a new method which considers both the local feature and global feature of gesture is introduced using Kinect sensor [2]. But the problem with this sensor is it's not support minute details like shape of hand. While considering fingerspell recognition, the main focus was on local features extraction for static sign. So experiments are performed using Leap Motion sensor to recognize signs in different languages. The ultimate aim of this research work is to assist the speech impaired people to convey their feelings to common people who don't understand sign language.

II. Related Work

The research work in mainly focus on tracking hand, capturing its positional features and matching it with database so as to translate sign language to text or spoken word. Some systems which uses sensors are as follows.

A. *Instrumented glove Based system*

Tushar Chouhan et al. [3] have achieved average accuracy of 96% over a data set of 200 examples (20 examples per gesture) was generated by taking the values for symbols 0-9 iteratively. Vasiliki E. Kosmidou et al. [4] proposed a analysis of the surface electromyogram (sEMG) signal for recognition of American Sign Language (ASL) gestures. Sixteen features are extracted from the sEMG signal acquired from the user's forearm, and evaluated by the Mahalanobis distance criterion. Discriminant analysis is used to reduce the number of features for classification of sign. The classification results reveal that 97.7% of the inspected ASL gestures were correctly recognized. Tan Tian Swee et al. [5] have designed a system that can recognize 25 common words signing in Bahasa Isyarat Malaysia (BIM) by using the Hidden Markov Models (HMM) method. A set of sensors consists of accelerometers and flexure sensors have been setup to capture the movement or gesture.

Wang et al. [6] in 2008 have recognized 14 postures of sign language using Multilayer architecture to speed up the search process using two Cyber Gloves and three Pohelmus 3 SPACEposition tracker as input devices. Features such as hand shapes, orientation, position, movement trajectory are extracted. The average recognition rates of 82.73% for HMM and 87.39% for multilayer architecture are observed for the registered test set. Different experiments for recognition of Chinese sign language carried by Zhou et al.[7] in year 2008 using Cybergloves and three Polhemus 3SPACE-position trackers as input devices. It is observed that accuracy conventional HMM methods is improved by 6.81% because of combination of PSM and Mahalanobis distance.

In 2008, Maebatake et al. [8] have proposed a sign language sentence recognition using Polhemus FASTRAK, a magneto metric sensor system. Sequence of both hands position and movements are used as features. These features are input to a multi-stream HMM. Experiment in conduced on 21,960 sign language word data. As a result, 75.6 % recognition accuracy was obtained. Pei Yin et al. [9] in 2009 recognized and identified top 10 similar signs of ASL using DIST-SBHMMs algorithm on the accelerometer based ASLR dataset. Using one three-state HMMs to model each sign, ASL phrases (words) are splited as 90% for training and 10% for testing. It is observed that recognition error is reduced by 9%.

In 2002, Chunli Wang et al. [10] have used system two CyberGloves and a Pohelmus 3-D tracker with three receivers positioned on the wrist of CyberGlove and the waist are used as input device to recognize continuous Chinese sign language recognition(CSL). The average recognition accuracy of 200 sentences using HMM is over 90%.However start and end of phoneme in sentence is not explained. Yun Li et al. [11] in 2011 have worked on Chinese Sign Language(CSL) recognition system to interpret sign components from ACC and sEMG data only. A 20-dimensional hand shape feature vector for each subword is collected through four channels. A fuzzy K-means algorithm is used to form cluster of hand shapes. A linear discriminant classifier (LDC) is trained to model the within-class density of each hand shape class as a Gaussian distribution. As movement classifier, multi-stream HMM (MSHMM) which combines the movement information described by ACC and sEMG features is used. 40 CSL sentences constituted by 175 frequently used CSL words, from which a vocabulary of 116 subwords was summarized. Each signer was required to perform these sentences in sequence with 3 repetitions per sentence. Recognition accuracy is improved from 95.2% at the subword level to 98.3% at the component level for Subject 1 and from 92.7% to 96.8% for subject 2.

Similar type of work carrier in 2012, Deen Ma et al. [12] have proposed Hidden Conditional Random Field (HCRF) for Sign Language Recognition (SLR) based on surface electromyography (sEMG) and acceleration (ACC) signals. Experiments conducted on five subjects and 120 high-frequencies used Chinese sign language (CSL) subwords obtained 91.51% averaged recognition accuracy. This result demonstrated that HCRF is feasible and effective for the sEMG and ACC based Sign Language Recognition. In 2014, Shinpei Igari et al. [13] in 2014 have used three-dimensional position measurement device Liberty (POLHEMUS Inc.) to measure JSL movements. Out of 80 words, 20 words belonged to “One-handed signs” and 60 words belonged to “Two-handed signs”. Using matching method by the classification based on the correlation between the movements of right and left arm, authors have achieved 98 % recognition rate. In 2015, José Emiliano López-Noriega et al. [14] have used 5DT gloves which has 5 sensor to recognize 26 alphabets. Using GUI few sentences are form by collecting word in window and played to generate audio output. However it is not mentioned that how sign like J and Z are handled which includes movement.

Similarly, Noor Tubaiz et al. [15] have recognized few sentence of Arabic Sign Language using data glove. Two DG5-VHand data gloves wear on two hand which captures hand movements. Feature set consists of readings represent the amount of bend in each finger, hand acceleration and orientation. The sensor readings at any time instance from both gloves are concatenated (appended) into one set of readings. Subsequently, a Modified k-Nearest Neighbor (MKNN) approach is used for classification. The proposed solution achieved a sentence recognition rate of 98.9%.

The only drawback of these types of systems is signer has to wear many sensors on wrist and arms which is hectic.

B. Leap Motion and Kinect sensor based system

In 2013,C. S. Weerasekera et al. [16] have proposed a robust approach for recognition of bare-handed static sign language. Local Binary Patterns (LBP) histogram features based on color and depth information, and also geometric features of the hand are used as features. Linear binary Support Vector Machine (SVM) classifiers are used for recognition. An accurate hand segmentation scheme using the Kinect depth sensor is also presented. The algorithm is tested on two ASL finger spelling datasets where overall classification rate over 90% are observed. It is also shown to be robust to changes in distance between the user and camera and can handle possible variations in finger spelling among different users.

Kinect sensor in two different ways is used to recognize PSL words in 2013 by Mariusz Oszust et al. [17]. In one approach PSL words are recognized using sensor Kinect and the nearest neighbor classifier. In another approach hand segmentation is done. It is observed that in second approach with KNN classifier proved to be best with recognition accuracy of 98.33% for 30 words.

In 2013, Harsh Vardhan Verma et al. [18] have proposed an isolated sign language recognition system where system works on recoded video. From recorded video, frames are separated and similar postures are grouped together using K-mean clustering. After this every gesture, which is a sequence of several postures, has now been reduced to a simple sequence of cluster IDs. The system was trained to identify ten different gestures (ten gestures in main dictionary), and then was tested with a dataset containing 150 test gestures and obtained average accuracy of 90.66%. Abbas Memis et al. [19] presents a Turkish Sign Language (TSL) recognition system which uses Motion difference based cumulative motion images. 2-D DCT is applied to cumulative sign images to obtain spatial features of signs & the energy density of signs in transformed images. Feature vectors are obtained from coefficients of DCT. For the recognition process K-Nearest Neighbor classifier with Manhattan distance is used. System performance is evaluated on a sign database that contains 1002 signs belongs to 111 words in three different categories where system recognition rate of 90% is obtained.

In 2013 Zhou Ren et al. [20] have used advanced sensors like Kinect to recognize signs from 1 to 10. The hand is detected using distance threshold. Using Template matching and Finger-Earth Mover's Distance (FEMD), experiments carried out which demonstrate that hand gesture recognition system is 93.2 % accurate. Although system is robust to hand articulations, distortions and orientation or scale changes, and can work in uncontrolled environments (cluttered backgrounds and lighting conditions) but Kinect sensor face difficult to detect and segment a small object like hand from an image due to low resolution (640×480). Geetha et al.[21] in 2013 proposed a work for recognizing dynamic signs corresponding to ISL words using Microsoft Kinect Local features such as 3D key points extracted. In local feature extraction the distance between each finger tip to centroid is computed. Twenty five key points are extracted from each gesture and the distance between those points to the all is computed. These distance vectors are taken as the global features. The method extracts features from the signs and converts it to the intended textual form.

In 2013, Chao Sun et al. [22] proposed a discriminative exemplar coding (DEC) approach for recognition of American sign language phrases using Kinect sensor. Hand motion feature are obtained by applying Optic flow (OP) method to one patch on a color frame and the patch in the same position on the previous frame resulting in hand motion feature of 2304 dimensions. Total feature vector is reduced to 300 dimensions using PCA. Then corresponding classifiers are trained for each sign pattern via mi-SVM. Later on AdaBoost is employed to form a strong classifier to classify signs.

A new feature extraction technique presented by Lucas Rioux-Maldague et al. [23] in 2014 for American Sign Language fingerspelling (alphabets except J and Z) hand pose recognition using depth and intensity images. Authors achieved 99 % recall and precision on the first, and 77 % recall and 79 % precision on the second.

In 2014, Saad Masood et al. [24] Presents a method for detecting, understanding and translating sign language gestures to vocal language. In proposed method DTW algorithm is applied to compare the gesture stored in linked list with the gesture stored in gesture dictionary which is capable of successfully detecting all gestures that do not involve finger movements. The proposed system has an accuracy of 91%. A.S.Elons et al. [25] in 2014 used Leap motion which captures hands and fingers movements in 3D digital format. The system using neural network (MLP) was tested on 50 different dynamic signs (distinguishable without nonmanual features) and the recognition accuracy reached 88% for two different persons.

In 2014, L. Nanni et al. [26] have proposed a hand gesture recognition system based on distance and curvature features computed on the hand shape that improves both in accuracy and reliability. They introduced novelties like an ensemble based on two different descriptors, extracted from 3D information. Each gesture is repeated 10 times for a total of 1000 different depth maps with related color images. In Second dataset 12 different gestures performed by 14 different people. Each gesture is repeated 10 times as in the previous case for a total of 1680 different depth maps with the corresponding color images. It is successfully implemented with recognition accuracy of 97.9 and 88.7 on two different datasets. In 2015, Cao Dong et al. [27] A segmented hand configuration is first obtained by using a depth contrast feature based per-pixel classification algorithm. To validate the performance of this method, they used a publicly available dataset from Surrey University. The results have shown that their method can achieve above 90% accuracy in recognizing 24 static ASL alphabet signs a color glove was designed in order to generate realistic training data conveniently. To improve the joint localization accuracy, they employed kinematic probabilities in the mode-seeking algorithm to constrain the joints within possible motion ranges. The assemblies of the 13 key angles of the hand skeleton were used as the features to describe hand gestures. A Random Forest (RF) gesture classifier was implemented in the end to recognize ASL signs. The system achieved a mean accuracy of 92% on a dataset containing 24 static alphabet signs.

In 2014, Giulio Marin et al. [28] proposed a novel hand gesture recognition scheme using Leap motion and Kinect. Feature set of leap Motion consists of Fingertips distances, Fingertips angles and Fingertips elevations. It is observed that due to combination of Leap and Kinect the recognition accuracy achieved is 91.28% for 10 static signs of ASL.

Makiko Funasaka et al. [29] recognized ASL alphabets except J and Z By using the decision tree using Leap Motion Controller. The constructed flowchart is differing as order of decisions, recognition rate for all letters change from the difference accuracy rate of decisions. For sorting of decisions enormous combination, genetic algorithm is applied to search for the optimal solution in the automatic construction of sign language recognition algorithm. The decision tree is automatically generated by a Genetic algorithm to obtain quasi-optimal solutions. Authors have performed several experiments for the application of the Genetic algorithm and obtained the quasi-optimal solution of the recognition rate 82.71%.

III. SYSTEM OVERVIEW

The Leap Motion controller is a small USB peripheral device which is designed to be placed on a physical desktop, facing upward. Using two monochromatic IR cameras and three infrared LEDs, the device observes a roughly hemispherical area, to a distance of about 1 meter. Leap Motion sensor is a small size sensor which is easy to use and of low cost as shown in Fig 1.

Fig. 1. Leap Motion Controller

This sensor not only tracks the hand movements but also it has the ability to distinguish the fingers' joints and track their movements.

IV. FEATURE SELECTION

Here 15 Euclidean distances are calculated for all combination of 6 points p1 to p6 as shown in Fig.2

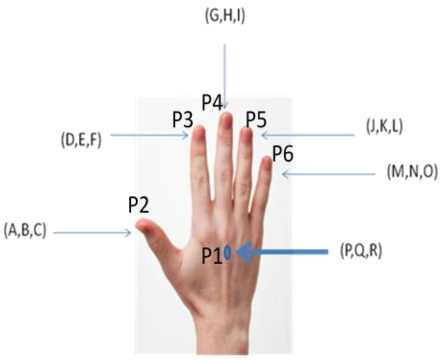


Fig. 2. 3-D points of hand

$$D1 = \sqrt{(P-A)^2 + (Q-B)^2 + (R-C)^2}$$
$$D2 = \sqrt{(P-D)^2 + (Q-E)^2 + (R-F)^2}$$
$$D3 = \sqrt{(P-G)^2 + (Q-H)^2 + (R-I)^2}$$
$$D4 = \sqrt{(P-J)^2 + (Q-K)^2 + (R-L)^2}$$
$$D5 = \sqrt{(P-M)^2 + (Q-N)^2 + (R-O)^2}$$
$$D6 = \sqrt{(A-D)^2 + (B-E)^2 + (C-F)^2}$$
$$D7 = \sqrt{(A-G)^2 + (B-H)^2 + (C-I)^2}$$
$$D8 = \sqrt{(A-J)^2 + (B-K)^2 + (C-L)^2}$$
$$D9 = \sqrt{(A-M)^2 + (B-N)^2 + (C-O)^2}$$
$$D10 = \sqrt{(D-G)^2 + (E-H)^2 + (F-I)^2}$$
$$D11 = \sqrt{(D-J)^2 + (E-K)^2 + (F-L)^2}$$
$$D12 = \sqrt{(D-M)^2 + (E-N)^2 + (F-O)^2}$$
$$D13 = \sqrt{(G-J)^2 + (H-K)^2 + (I-L)^2}$$
$$D14 = \sqrt{(G-M)^2 + (H-N)^2 + (I-O)^2}$$
$$D15 = \sqrt{(J-M)^2 + (K-N)^2 + (L-O)^2}$$

Similarly a Cosine angle between every two positional values is calculated as shown below for all possible combination of point p1 to p6. As an example, cosine angle between point p1 and p2 is calculated as

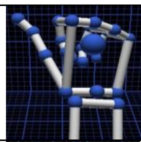
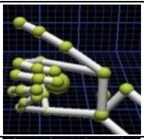
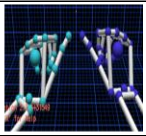
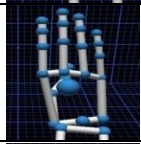
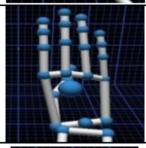
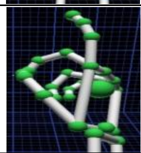
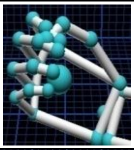
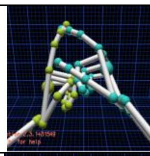
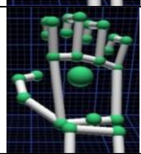
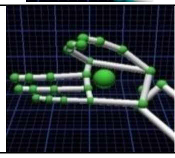
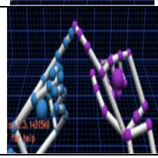
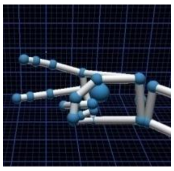
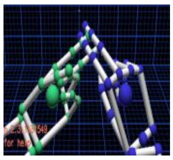
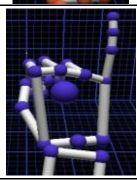
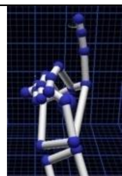
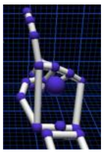
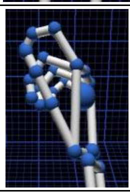
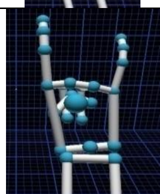
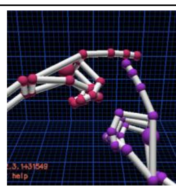
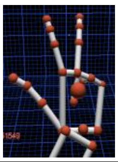
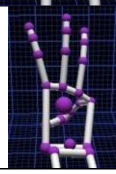
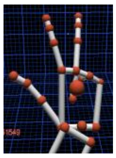
Costheta1=dot(P1,P2)/(norm(P1)*norm(P2))

thetha_deg1= acos (Costheta1)*180/pi

Likewise for all possible combination of point p1 to p6, total 15 angles (thetha_deg1, thetha_deg2,...,…,…, thetha_deg15) are calculated.

Some samples for different languages as they appear on Visualizer tool of Leap motion sensor is shown in Table 1.

Table 1: Sign samples on Visualizer of Leap Motion

Sign	Sign Language		
	ASL	CSL	ISL
A			
B			
D			
E			
F			
I			
T			
5			

V. DATASET

A. Dataset and feature selection for ASL recognition

Signs are collected from 146 users who have performed 32 signs (as shown in Table 2) once resulting in total dataset of 4672 signs. The feature set consists of positional values of each finger and palm, distance between positional values, angle between positional vales with respect to plane. Understanding the fact that every person has different hand shape and size, a database is created so as to have all possible samples of hand pose for concern posture. Here 15 Euclidean distances are calculated for all combination of 6 points p1 to p6 as shown in Fig.2.

Thus for one sign, got 18 positional values, 15 distance values and 15 angle values resulting in feature vector of size 48. This way for all signs feature matrix of size 4672 × 48 is obtained.

B. Dataset and feature selection for CSL recognition

Dataset consists of signs performed by 100 signers (students of age 20-22 years) who have given training about how to perform signs. Total 34 signs are considered as shown in Table 2. Every signer has performed each sign only once which results in total dataset of 3400 signs. Same features as explained for ASL are used here. This way for all signs got the feature matrix of size 3400 × 48.

C. Dataset and feature selection for ISL recognition

Ten students have performed 33 signs as shown in Table 2. Each sign is repeated 10 times. So obtained the feature matrix of size 3300 × 97 for all 33 signs. Features like distance and angle as explained for ASL in Section 4.3.4.1 are used. However few signs required two hands to perform sign. Thus for one hand, got 48 values (18 positional values, 15 distance values and 15 angle values). Similarly for another hand got 48 values. Distance between center of palm of two hand is also calculated which results in total feature set of 97 values. If the sign is performed using only one hand then features of second hand are considered as zero value and distance between center of palm for two hands is considered as very large, in experiment it is fixed as 5000.

Table 2: Summary of dataset

Sign Language	**Signs considered**	**Signs not considered Due to similar postures**
ASL	1,3,4,5,7,8,9,10 A,B,C,D,E,F G,H,I,K,L,M, N,O,P,Q,R,S, T,U,V,W,X,Y	2,6 as 2 = V 6 = W
CSL	1,4,5,7,A,B,C,D, E,F,G,H, I,J,K,L, M,N,O,P,Q,R,S, T,U,V,W,XY,Z, ZH,SH,NG,CH	2,3,6,8,9 as 2 = V, 3 = W 6 = Y, 8 = L 9 = J
ISL	3,4,5,6,7,8,9,A,B C,D,E,F,G,H,I,J,K L,M,NO,P,Q,R,S T,U,V,W,X,Y,Z	0,1,2 as 0 = O,1 = I, 2 = V

VI. RESULTS

While experimentation 90% data is used for Training & 10% for Cross validation. It is observed that only one hidden layer was enough to get satisfactory results. The following results are obtained using "Neurosolutions 5.0", a neural network development tool. Only those neural network's results are quoted which have given best results compared to others.

A. Results on ASL dataset

Multilayer Perceptron Neural network (MLP) with the following parameter setting gives maximum Percentage classification accuracy of 92.66 % on training and 90 % on CV dataset.

Input Layer:
Processing Element (PE): 48 Exemplars: 4205

Hidden Layer:
Processing Elements: 27 Transfer Function:- Tanh
Learning Rule: Conjugate Gradient

Output Layer:
Processing Element (PE): 32 Transfer Function:- Tanh
Learning Rule: Conjugate Gradient

B. Results on CSL dataset

After experimentation it is observed that the best results are obtained as 99.97 % on training and 93.11% on CV data set using Support Vector Machine neural network (SVM) with optimal parameter setting as below.

Exemplars: 3060 No. of Epoch: 17
Input PEs: 48 Output PEs: 32 Step Size: 0.3
Kernel Algorithm: Adatron

C. Results on ISL dataset

Generalized Feed Forward neural network (GFF) with the following parameter setting gives maximum Percentage classification accuracy of 97.34 % on training and 96.36 % on CV dataset.

Input Layer:
Processing Element: 97 Exemplars: 2970

Hidden Layer:
Processing Elements:13 Transfer Function: Tanh
Learning Rule: Momentum Momentum: 0.7
Step Size: 0.1

Output Layer:
PE's:34 Transfer Function - Tanh Momentum - 0.7
Learning Rule - Momentum Step Size - 0.1

However it is also observed during experimentation that MLP neural network performs equally well for all three sign language recognition.

As the Leap Motion works on skeleton of hand, the system based on this sensor has no need of signer to wear any special hardware device or do not need to worry about environmental constraints.

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