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Performance Analysis of different Classifiers for Chinese Sign Language Recognition

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Abstract: *The Chinese Sign Language alpha-numeric character recognition without using any embedded sensor or color glove or without the constraints of environment is really difficult task. This paper describes a novel method to use leap Motion sensor for static sign recognition by obtaining feature set based on hand position, distance and angle between different points of hand. Feature set is later trained and tested using different classifiers like MLP (Multilayer Perceptron), GFFNN (Generalized Feed forward Neural Network), SVM (Support Vector Machine). We have collected dataset from 100 people including students of age 20-22 years and few elders age between 22-35 who have performed 34 signs (30 alphabets & 4 numbers) resulting in total dataset of 3400 signs. Out of this 90% dataset is used for training and 10% dataset is used for testing/Cross validation. we have got maximum classification accuracy as 93.11% on CV/testing dataset using SVM Neural Network.*
Keywords: *CSL,MLP,GFFNN,SVM*

I. Introduction

The number of deaf people in the world is approximately 70 million. Sign Language is mainly used by deaf-mutes to communicate with each other. Communication in this language is through gestures and visions. As sign languages are non-verbal languages, information is conveyed visually, using a combination of manual and non-manual means of expression. Manual parameters are hand shape, hand posture, hand location, and hand motion. The non manual parameters include head and body posture, facial expression, gaze and lip patterns. Sign Language recognition Systems are mainly categorized in two classes as instrumented/Data Glove based and vision (Camera) based. However a combination of both is also tied by researchers. It is observed that hardware (Instrumented glove/Data Glove) based systems can recognize sign more correctly than vision as it has direct information of positioning of fingers and hand movement in coordinate format. Object identification is not the issue in instrumented based system as sensors are directly mounted on elbow, hand, fingers etc.

In comparison to this, vision based system need to first identify the object from an image based on color space selection may be based on skin color or color glove used in segmentation process. Skin color based segmentation is mainly done with plain background or with cloths of dark color where complete hand is covered and only palm, fingers are uncovered. However due to advancement in technology new devices like Leap Motion Sensor & Kinect, researchers have no barrier of background as expected depth can be programmed and 3D information with RGB color information solves most of the problems in traditional methods of sign language recognition.

II. Previous Work

Most of the research work in sign language recognition system is concern to translation of sign language to text or spoken word. Some systems are as follows.

A. Vision Based system

In Vision based system the hand is segmented using color space like RGB, YCbCr, HSV and used skin color as base. In 2007 [5] Yikai Fang et al. have proposed a robust real-time hand gesture recognition method . A specific gesture is used to trigger the hand detection followed by tracking. Hand detection uses extended Adaboost method which adopts a new type of featurefour box. Hand tracking is achieved using multi-modal technique which combines optical flow and color cue to obtain stable hand tracking. Hand is segmented using single Gaussian model to describe hand color in HSV color space. From the image multi-scale feature across binary image is calculated. Fourier transform of sample hand image and neutral grey image of the same size is used to find reparability values. Applying the proposed method to navigation of image browsing, experimental results shows that the average accuracy of six gestures recognition is 93.8%.

In 2012 [6], Serban Oprisescu et al. proposed an automatic algorithm for static hand gesture recognition relying on both depth and intensity information provided by a time-of-flight (ToF) camera. The combined depth and intensity information facilitates the segmentation process, even in the presence of a cluttered background (2 misses out of 450 images). Hand is segmented using region growing algorithm using distance property. Gesture classification is based on a decision tree using structural descriptions of partitioned contour segments. Classification was tested on 9 different gestures (1 to 9). The final mean recognition rate is about 93.3%. In 2014 [7], Jingzhong Wang, Meng Li. have recognized 30 finger gestures recognition of Chinese phonetic alphabet using contour features. Three sets of gesture library was created. Each set consists of 30 finger gestures performed five times of size 640*480 as a bitmap image. Thus total 450 gesture dataset is used. Out of three library set one set is used as a sample set and two sets as test set. After images pre-processing, edge features and contour characteristics are used as for matching. The results show that this method can carry out classification efficiently of 30 sign language gestures, and its recognition rate reaches 93%.

B. Instrumented glove based system

Despite lots of research work carried out using traditional vision-based hand gesture recognition methods [1]–[3] they are still far away fror real-life applications. Optical sensing based system are mainly fail due to poor lightening conditions and cluttered backgrounds. So these methods are usually unable to detect and track the hands robustly, which degrades the performance of hand gesture recognition. Using instrumented glove, In 2002[7], Chunli Wang 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 raw gesture data include hand postures, positions and orientations. Total 2400 phonemes are defined for CSL & One HMM is built for each phoneme. Experiments on a 5119 sign vocabulary are carried out which gives accuracy of 92.8 %.

In 2011,[8] Yun Li et al. have worked on Chinese Sign Language(CSL) recognition system to interpret sign components from ACC and sEMG data only. Three basic components hand shape, orientation and movement have been analyzed to identify gesture. A 20-dimensional hand shape feature vector (denoted as $\boldsymbol{\theta}$) for each subword is collected through four channels (3-axis ACC and 4 EMG sensors placed around forearms of one hand. A fuzzy K-means algorithm is used to form cluster of hand shapes. A linear discriminant classifier 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. The first two repetitions of each sentence were used to form training dataset and the last one was used for the test. 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 [9], Deen Ma et al. have proposed Hidden Conditional Random Field for Sign Language Recognition (SLR) based on surface electromyography (sEMG) and acceleration (ACC) signals. In the proposed method, after the periods of data acquisition, data segmentation, feature extraction, and preliminary recognition on the decision-tree level, HCRF was utilized in the bottom layer to classify an observation sequence into a specific class. 4 sEMG & one 3-D accelerometer placed on wrist to acquire data for words. Experiments conducted on five subjects and 120 high-frequency used Chinese sign language 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. These data glove based systems are sometimes inconvenient to use and may hamper the natural articulation of hand gesture. Also, such data gloves are usually more expensive than optical sensors, e.g., cameras. As a result, it is gains less popularity.

However due to recent development of inexpensive depth cameras, e.g., the Kinect sensor & Leap Motion, new opportunities opened doors for hand gesture recognition. In 2013 [10], Zhou Ren et al. have used advanced sensors like Kinect to recognize signs from 1 to 10. The hand is detected using distance threshold. Using one black color belt wear on wrist, hand shape is extracted. Later hand shape is represented as a time-series curve. Using Template matching and Finger-Earth Mover's Distance , 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). So segmentation of the hand is usually inaccurate, thus may significantly affect the recognition step. A.S.Elons et al. [11] have captured hands and fingers movements in 3D digital format using Leap motion. The sensor throws 3D digital information in each frame of movement. These temporal and spatial features are fed into a Multi-layer perceptron Neural Network (MLP). The system was tested on 50 different dynamic signs (distinguishable without non manual features) and the recognition accuracy reached 88% for two different persons.

III. Experiment

A. Data collection

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 [16]. Leap Motion sensor is a small size sensor which is easy to use and of low cost.

Fig.1. Leap Motion Sensor with inclination adjustment stand

This sensor not only tracks the hand movements but also it has the ability to distinguish the finger's joints and track their movements. While using Leap Motion, it is kept 10 degrees inclined as shown in Fig 1.

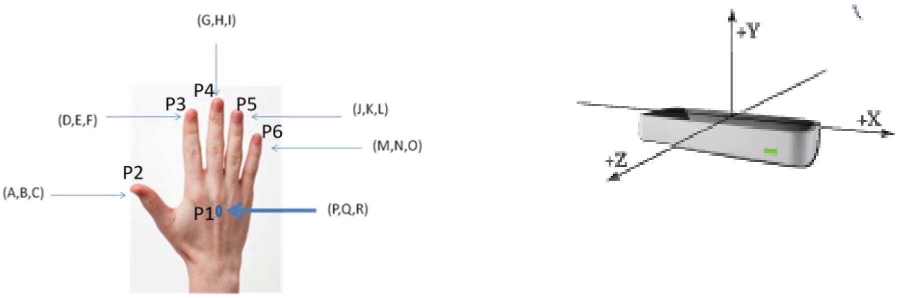

Fig.2. Data Acquisition through Leap Motion Sensor

Samples of signs on Visualizer tool of Leap Motion Sensor is shown in Fig. 3.

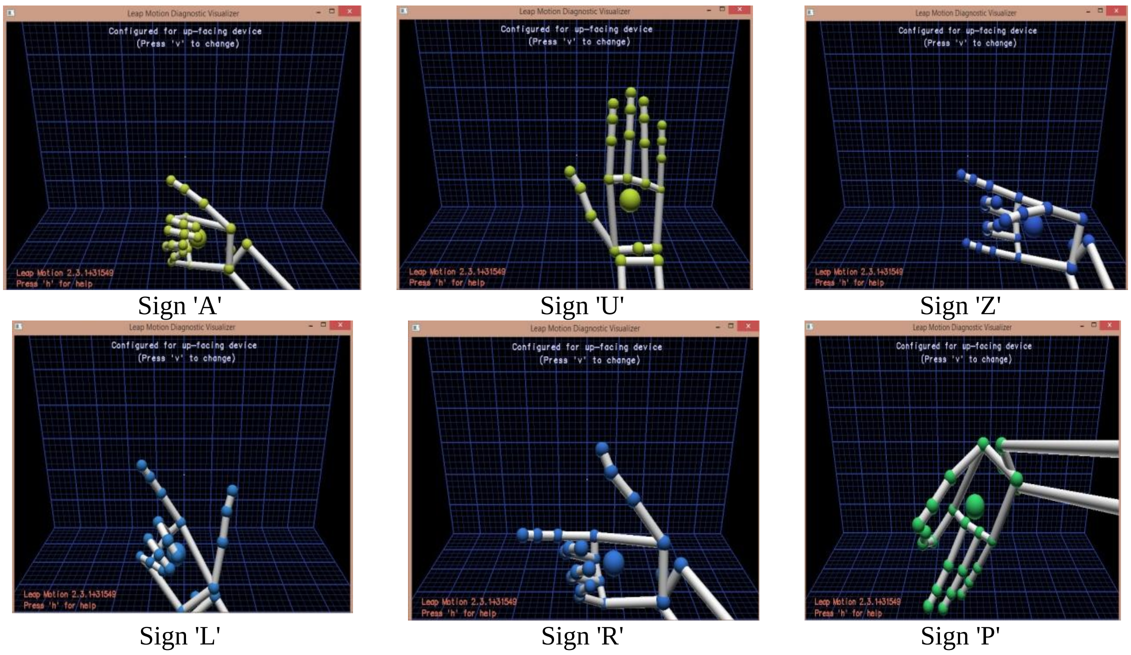

Fig.3. Sample of Signs on Visualizer Tool

As shown in Fig. 2, the 3D co-ordinates of finger tip and palm is accessed using Leap Motion API. We have collected signs from 100 users who have performed 34 signs resulting in total dataset of 3400 signs.

B. Feature extraction

The feature set consists of positional values of 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.

$$D1 = \sqrt{(P-A)^2 + (Q-B)^2 + (R-C)^2} \quad (1)$$
$$D2 = \sqrt{(P-D)^2 + (Q-E)^2 + (R-F)^2} \quad (2)$$
$$D3 = \sqrt{(P-G)^2 + (Q-H)^2 + (R-I)^2} \quad (3)$$
$$D4 = \sqrt{(P-J)^2 + (Q-K)^2 + (R-L)^2} \quad (4)$$
$$D5 = \sqrt{(P-M)^2 + (Q-N)^2 + (R-O)^2} \quad (5)$$
$$D6 = \sqrt{(A-D)^2 + (B-E)^2 + (C-F)^2} \quad (6)$$
$$D7 = \sqrt{(A-G)^2 + (B-H)^2 + (C-I)^2} \quad (7)$$
$$D8 = \sqrt{(A-J)^2 + (B-K)^2 + (C-L)^2} \quad (8)$$
$$D9 = \sqrt{(A-M)^2 + (B-N)^2 + (C-O)^2} \quad (9)$$
$$D10 = \sqrt{(D-G)^2 + (E-H)^2 + (F-I)^2} \quad (10)$$
$$D11 = \sqrt{(D-J)^2 + (E-K)^2 + (F-L)^2} \quad (11)$$
$$D12 = \sqrt{(D-M)^2 + (E-N)^2 + (F-O)^2} \quad (12)$$
$$D13 = \sqrt{(G-J)^2 + (H-K)^2 + (I-L)^2} \quad (13)$$
$$D14 = \sqrt{(G-M)^2 + (H-N)^2 + (I-O)^2} \quad (14)$$
$$D15 = \sqrt{(J-M)^2 + (K-N)^2 + (L-O)^2} \quad (15)$$

Similarly angles between every two positional values is calculated as shown below

Costheta1=dot(P1,P2)/(norm(P1)*norm(P2)) (16)
thetha_deg1=acos(Costheta1)*180/pi (17)

Likewise for all possible combination of point p1 to p6, total 15 angles(thetha_deg1, thetha_deg2,... thetha_deg15) are calculated. Thus for one sign we get 18 positional values, 15 distance values and 15 angle values resulting in feature vector of size 48. This way for all signs we get matrix of 3400 × 48.

C. Classification

1. Multilayer Perceptron Neural Network

Following trials have been performed on Multilayer Perceptron Neural Network (MLP) to get optimal parameters for minimum MSE and maximum percentage Average Classification Accuracy. Feature vectors are divided into two part as 90 % for training (TR) and 10% for Cross validation (CV). By keeping only one hidden layer, first network is tested to search number of Processing Element (PE) required in Hidden Layer which gives minimum Mean Square Error (MSE) on training dataset. Fig. 5 shows that minimum MSE is given by processing element (PE) number 30 but 17 numbered PE is selected because of very small MSE variation in comparison & to optimize the network parameter.

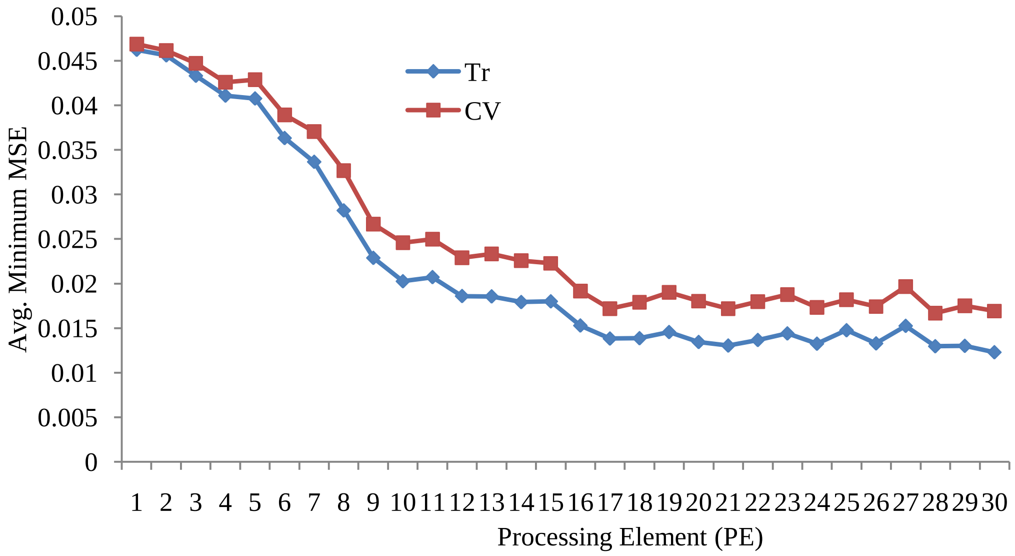

Fig.5. Processing Element (PE) Vs Minimum MSE

Different transfer function like Tanh, LinearTanh, Sigmoid, LinearSigmoid, Softmax and Learning rules like Step, Momentum, Conjugate Gradient, Quick Propagation, Delta Bar Delta are varied in hidden Layer to get maximum percentage classification accuracy as shown in Fig. 6.

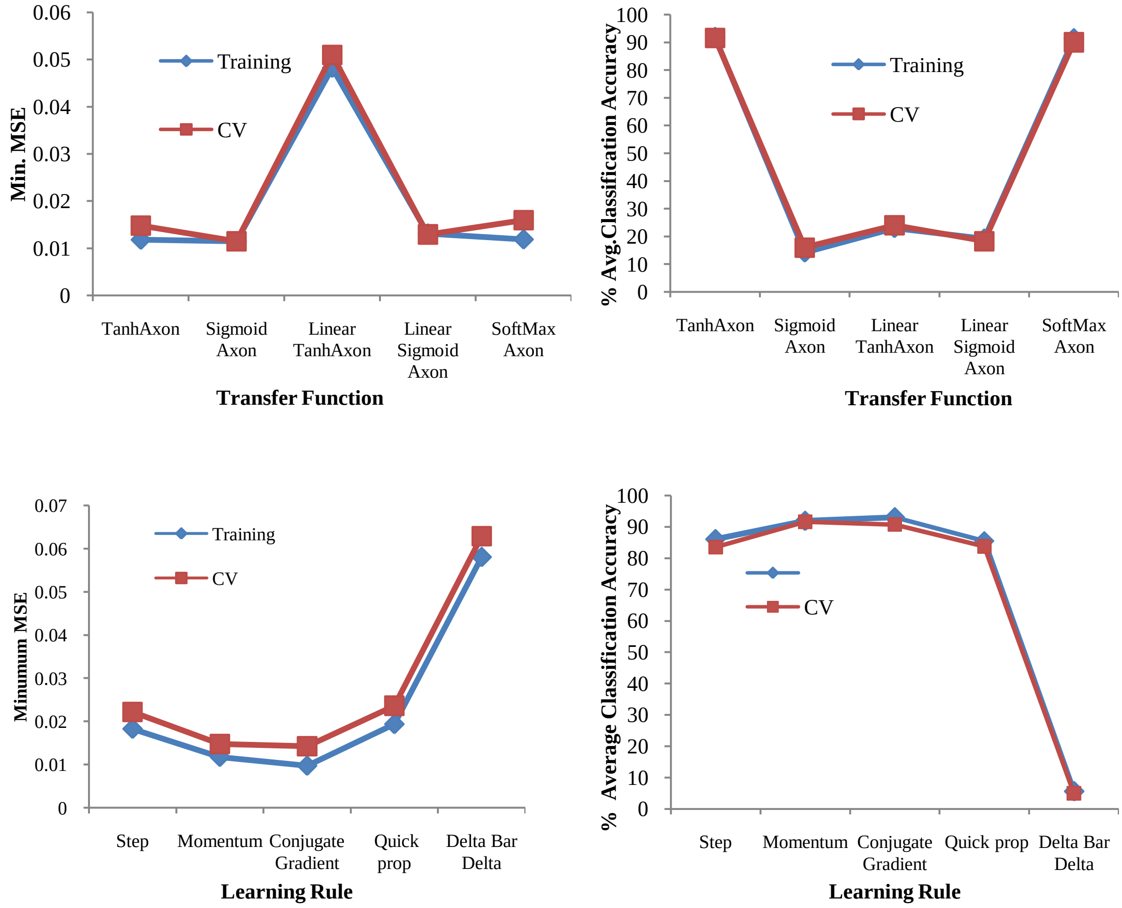

Fig. 6. Variation of Minimum MSE and Percentage average classification accuracy with different transfer functions and learning rules

MLP with the following parameter setting gives maximum Percentage classification accuracy of 91.87 % on training and 91.64 % on CV dataset. Tagging of Data: 90% for Training & 10% Cross validation

Input Layer:
Input Processing Element: 48 Exemplars: 3060
Hidden Layer:
Processing Elements: 17 Transfer Function: Tanh Learning Rule: Momentum
Momentum: 0.7 Step Size: 0.1
Output Layer:
Output PE's:34 Transfer Function: Tanh Learning Rule: Momentum Momentum: 0.7 Step Size: 0.1

2. Generalized Feed Forward Neural Network

Like MLP Neural Network we have performed similar trials using GFFNN. With the following parameter setting we have got maximum Percentage classification accuracy of 94 % on training and 92.40% on CV dataset. Tagging of Data: 90% for Training & 10% Cross validation.

Input Layer:
Input Processing Element: 48 Exemplars: 3060
Hidden Layer:
Processing Elements: 27 Transfer Function: Tanh Learning Rule: Momentum
Momentum: 0.7 Step Size: 0.2
Output Layer:
Output PE's:34 Transfer Function: Tanh Learning Rule: Momentum Momentum: 0.7 Step Size: 0.2

3. Support Vector Machine

We have varied epoch & number of runs by fixing the step size at 0.1. It is observed that from epoch 17 onwards, there is very small change is MSE as shown in Fig 7.

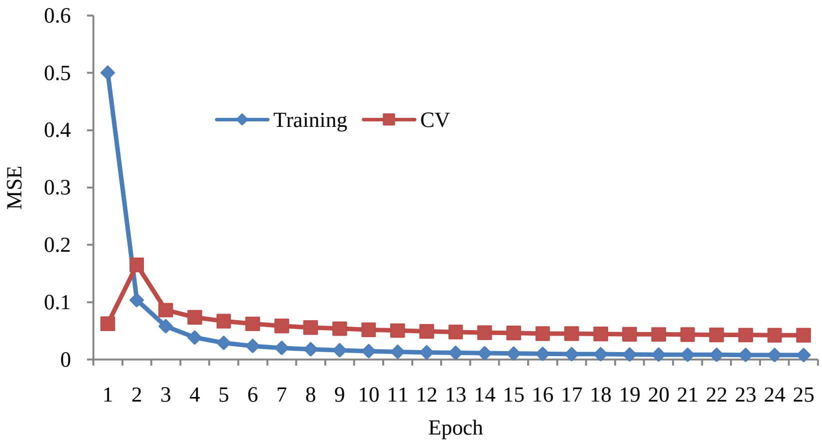

Fig. 7 Epoch Vs MSE

After fixing number of Epochs as 17, we have varied step size from 0.1 to 1 and plotted the Minimum MSE & percentage of classification accuracy as shown in Fig. 8

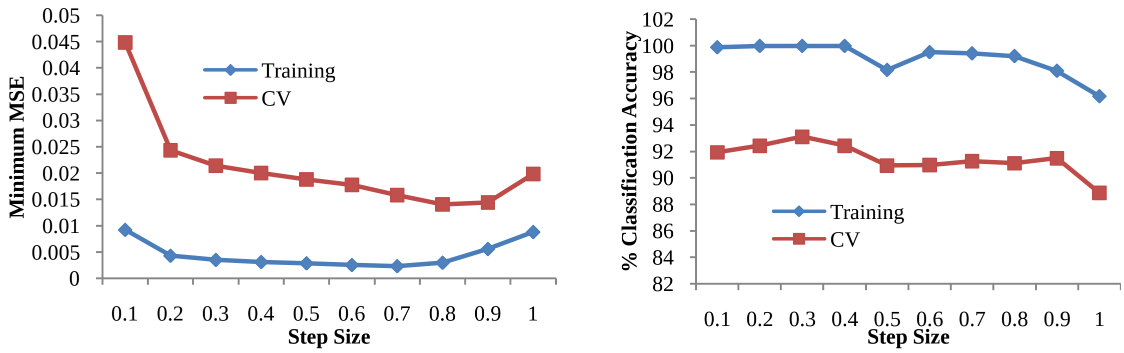

Fig.8. Step Size Vs Minimum MSE & Percentage classification Accuracy

After experimentation we have observed that the best result is i.e. 99.97 % on training and 93.11% on CV data set with optimal parameter setting as below
Tagging of Data: 90% for Training & 10% Cross validation
No. of Epoch: 17 No. of Runs: 1 Input Processing Elements: 48 Output Processing Elements: 32
Exemplars: 3060 Step Size: 0.3 Kernel Algorithm: Adatron

Table 1. Confusion Matrix for Cross Validation (CV)/Testing data set using SVM Neural Network

Output / Desired	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	X	Y	Z	ZH	SH	NG	CH
1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	13	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	0	0	0	0	9	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0
C	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
D	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	1	0	7	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	1	0	0	0	0	0	0	11	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	1
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0
W	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	9	0	0	0	0	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	8	0	0	0	0	0
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0
ZH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0
SH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
NG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0
CH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9

Table 2. Performance Matrix for Cross Validation (CV)/Testing data set using SVM

Sign	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	X	Y	Z	ZH	SH	NG	CH
% Correct Classification	100	100	92.9	100	100	90	88	100	83.3	100	100	100	92.9	91.7	76.9	100	92.3	90	85.7	100	100	53.9	77.8	100	100	88	100	81.8	100	100	100	100	100	81.8

Table 3: Performance measure of different classifiers

Sr. No.	Classifier	% Average Classification Accuracy	
		Training	CV
1	MLP	91.87	91.64
2	GFF	94	92.40
3	SVM	99.97	93.11

IV. Result

We have obtained maximum Average classification accuracy as 93.11 % on Cross Validation data with the optimal parameter setting as explained earlier using SVM Neural network as shown in Table 3. While comparing our result with other researcher Giulio Marin et al. [12] had received 80.86% overall accuracy for 10 signs by using leap motion sensor. It can be observed from confusion matrix shown in Table 1 that signs 'R' has only 53.9% classification accuracy and it is confused with sign 'L'. Although the postures of signs 'R' and 'L' are different but relative distances and angular measures are similar as can be observed from Fig. 3. So these signs pull down the overall classification accuracy as shown in Table 2. We have not considered few signs like 2,3,6,8,9 because these signs have similar postures like V,W,Y,L,J respectively.

V. Conclusion

Finally we came to conclude that although SVM classifier gives average 93.11% classification accuracy but still to improve the accuracy for sign like C,E,K,S,O,R,X.CH other important features of sign can be extracted and other classifiers can be tested.

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