Recognition and Analysis of Indian Sign Language Using Improved K-means Algorithm

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***Abstract*:**

In this paper, we recognize Indian Sign Language using gyroscope and accelerometer. The gestures are collected using gyroscope and accelerometer, which is fitted on both the arms of the signer. Gyroscope captures the arm and hand rotation gestures accurately and the accelerometer measures gestures related to vibrations. The obtained gestures are evaluated based on amplitude levels as approved gestures and unapproved gestures.The gesture with high accuracy is extracted from the approved gestures by means of feature extraction technique, where we fix the scale using prior initial values. Min-max scaling method is used in the extraction technique. A particular feature is selected and the selected feature from the dataset is subjected to improved K – means algorithm where clusters are formed. Based on this cluster a classifier is implemented which uses the distance probability technique and thereby the accuracy of the selected feature is found. The algorithm based on inertial sensors produces an accuracy of 96.55% for alphabets and 76.8% for sub words the static gestures are recognized effectively by the hand orientation and improved k-means classifier than the continuous gestures

Keywords: Accelerometer, Cluster, Distance Probability, Gesture, Gyroscope, Indian Sign language, K-means, Sensor fusion

1. INTRODUCTION

Communication is an important tool among humans. Early man used sign language when there was no appropriate language among them. Now, Sign language is most useful among differently abled people. It removes barriers faced by the deaf and dumb people in the society. Sign language enable the physically challenged to express their views with the normal people who cannot understand their gesture actions. To remove the barriers between the normal people and the differently abled people sign language recognition techniques are used. Sign language helps differently abled people to be comfortable in places like banks, booking counters, shops etc.; by communicating with the normal people [1] .Sign, language recognition (SLR) is a tool that converts language in to text or voice. By doing this conversion the problem, arising between deaf and dumb people and normal people is avoided. Capturing the gestures is the main aim in Sign language recognition. Two major techniques used to capture the sign languages are Glove based and Vision based Sign Language Recognition (SLR) techniques.

In Glove based technique, flex sensors will detect the gestures. Due to the expensive nature of glove devices, glove based techniques are not considered for usage. In Vision based technique, a Kinect camera and Image Processing concept will detect gestures. The mounted cameras suffers from a restricted range of visión moreover the required infrastructure availability in all the desired locations is less and it is too expensive to carry out [2].

Recognition of different alphabets of ISL in video sequences comprises of three stages, pre-processing, extraction and classification. Features includes good accuracy, bare hands usage, recognizes single and both hands but background illumination is one of the major drawback of this system [3].StrinGlove obtains full degrees of freedom of human hand using 24 induct coders and 9 contact sensor and encodes hand posture in to posture codes on its own DSP [4].The major drawback of this system is discomfort for the user. Built in Resistance sensor and ADXL335621X accelerometer in the hand gloves, uses

microcontroller to recognize the gestures and the android device converts the recognized gestures in to voice and text .The major drawback is correlation of sensors and design complexity[5].

Tracking the glove with a printed custom model also recognizes the gestures using a single camera. This design eliminates pose estimation problem but calculates only limited number of gestures [6].With the help of canny algorithm the numeral value of opened fingers in a gesture is identified. But representing a gesture with closed finger is not accurate using this method. [7].A robust part-based hand gesture recognition using kinect sensors demonstrates the usage of human hand as a natural and an intuitive way to interact with the machines and it is also robust to distortion but its accuracy is not satisfied during the usage of similar orientation for certain gestures [8].

Because of reduced cost, low power consumption and an ever-present sensing ability wearable sensor based gesture recognition captures researchers consideration [9], [10]. Accelerometer captures acceleration and gyroscope measures angular velocities. These IMU sensors worn in the hands are excellent in measuring hand orientation. The fusion of accelerometer and gyroscope will enhance the recognition performance of an SLR system [2.]

This paper explores the recognition of Indian sign language using inertial sensors namely accelerometer and gyroscope. Although such a system has been studied for Chinese sign language [11], to the best of the authors' knowledge this is the first time such a system is studied for Indian sign language.In our work Feature extraction technique using accelerometer and gyroscope is proposed. Improved k-means algorithm is evaluated for intra subject testing and the accuracy.

2. PROPOSED METHODOLOGY

Indian sign language recognition technique carried out in this work is shown in Figure.1. Three axis accelerometer captures the gesture data based on hand vibration and a three axis gyroscope captures the data based on hand rotation. We use these inertial sensors as the input device on both hands to capture the gestures. Each sensor will give three values, totally 12 measurable values are obtained. The sensors generate analog signals and these signals are sent to the hardware module. In the hardware module digital form of the signal is constructed.

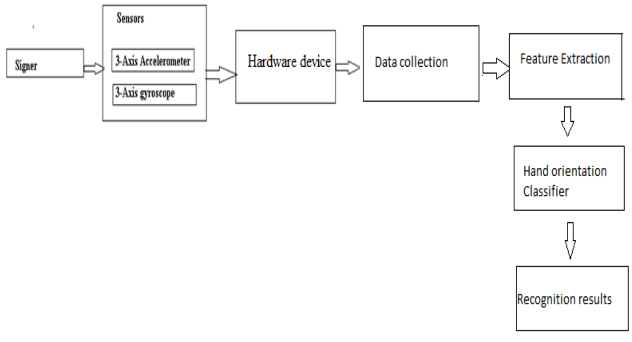


Figure.1.Block diagram

The obtained data in terms of amplitude is sent through the hyper terminal to the data collection unit. The collected data contains all different form of information due to the hand movement. From the collected data set the approved data is chosen. The approved data is selected with the aid of feature extraction technique. The average value of the approved gestures gives the hand orientation of the static and dynamic gestures. Then the hand oriented data sets are subjected to improved K-means algorithm in the classifier to get high accuracy. The hardware implementation model is detailed in figure 2.

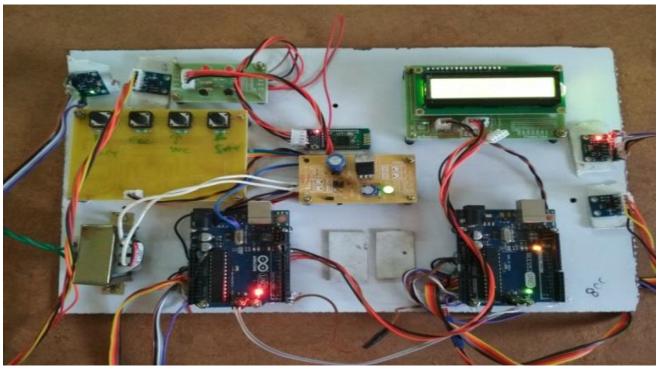


Figure.2.Hardware module

3. EXPERIMENTAL SETUP

3.1 Sensor Placement

The Indian sign language may require the use of either one hand or both hands. In our paper, we experiment with both hand movements. If the system is deployed on two hands, it will increase the recognition accuracy. Here we use a pair of sensors namely accelerometer and gyroscope. Gyroscope sensor is placed in the forearm and the accelerometer sensor is placed above the wrist.

3.2 Data Collection

Indian sign language contains alphabets, words, sub-words, and sentences. ISL is classified in terms of static and dynamic. Static gesture is a fixed gesture where the dynamic gesture is a movable gesture. Both static and dynamic is considered in this work that includes 26 alphabets and 2 sub words. The gesture action is performed by 8 subjects for the first 6 alphabets (A to F). Each subject has different muscle strength and hand shape. Individually the subject performs the gesture action 3 times repeatedly. All these subjects are first-time learners and do not know ISL before. The gesture action performed by 8 subjects thrice for first 6 alphabets produces 96 instances. The remaining alphabets (G to Z), gesture action is done by 3 subjects and again each subject performs the gesture 3 times repeatedly. Now the total data set of the remaining alphabets from G to Z is 108 instances. Finally we have two sub words and the gesture action for each sub-word is repeated three times by 3 subjects and now the total number of instances for the sub words is 21.Each instance contains 12 digital data which is obtained from the inertial sensors on both hands.

3.3. Feature Extraction

The inertial sensors produces data, when the subject performs gesture action. This data includes both approved and unapproved gestures. From the obtained data sets an approved set of gesture must be selected. Min –max scaling method is applied to choose approved gestures using amplitude variations. The amplitude variations of inertial sensors is compared with a fixed optimal value. The amplitude values above the fixed optimal value is termed as approved gestures and those that falls below the optimal value are considered as unwanted gestures.The Indian sign language may require the use of either single arm or two arms. In our paper, we experiment with both arm movements. If the system is deployed on two hands, it will increase the recognition accuracy. A pair of sensors is used namely accelerometer and gyroscope. Gyroscope sensor is placed in the forearm and the accelerometer sensor is placed above the wrist.

3.4. Hand Orientation Classifier

The hand orientation is characterized by the following two terms such as (i)in which direction the hand and the arm are pointing (ii) the facing of palm. The inertial sensors which includes both accelerometer and gyroscope is placed on the arm. Due to various hand orientation different values are obtained along the 3 axes inertial sensors. From the obtained values, set of approved gesture is chosen by feature extraction method. The average value of the approved gestures along the 3 axes inertial sensors reflects the hand orientation of the static and dynamic gestures. With the hand orientation data, three clusters are formed with the approved gesture sets. In this work we initiate improved K means clustering algorithm for grouping the clusters. Distance probability classifier technique is used for finding the accuracy of the gestures.

3.5 Classification Results

The data from the signer is exposed to classification. The static and dynamic gestures are classified separately using distance probability classifier algorithm to obtain accuracy. In our work the accuracy is calculated for all the approved gestures using improved form of k means grouping algorithm and finally the mean value of the accuracies is calculated. With this distance probability technique the overall exactness achieved for static gestures is 96.55% and 76.8% for dynamic gestures. ISL recognition using inertial sensors are more convenient for application than the vision based method

4. EXPERIMENTAL RESULTS

The gesture action for the Indian sign language alphabets is shown in Figure3. Two different experiments are performed to assess the system that is data collected from the same subject and from the different subjects. The collected data from the two different experiments are put together. These experiments produce two data forms such as training data set and testing data set. The hardware module can be tested both online and offline. In this paper, we concentrate only on offline tests. From that, we evaluate the accuracy of the gesture recognition

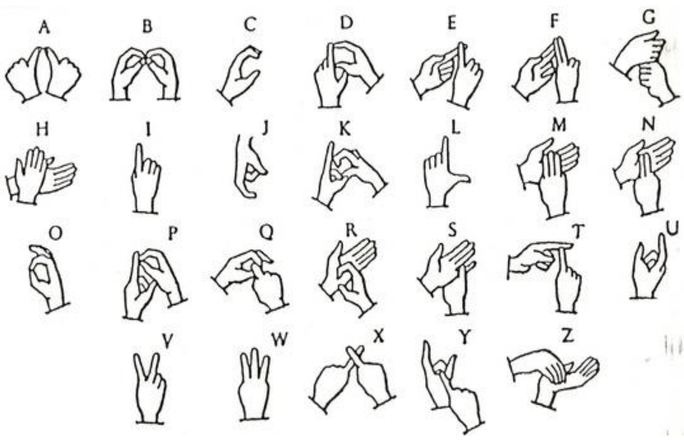
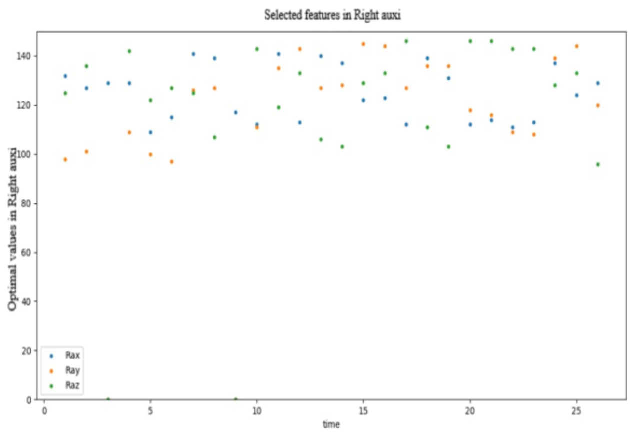


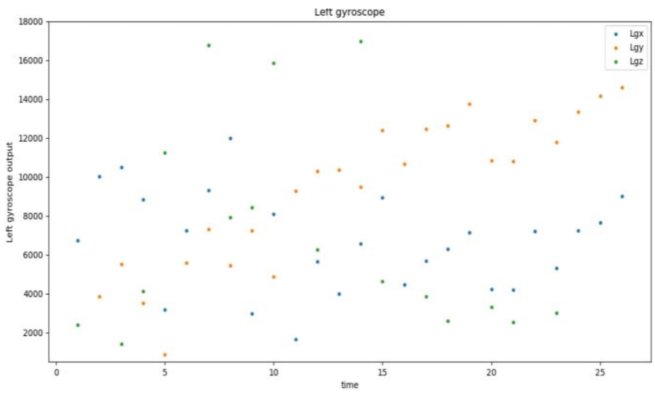
Figure.3. Indian Sign Language Alphabets

4.1.Feature Extraction

Feature extraction provides a way to select the appropriate feature subset for certain tasks from the well established features. It reduces over fitting problems and information redundancy existing in the feature set. There are three different feature selection methods, which are filter methods, wrapper methods and embedded methods [12].Wrapper methods weighs each feature subset based on a specific predictive model.



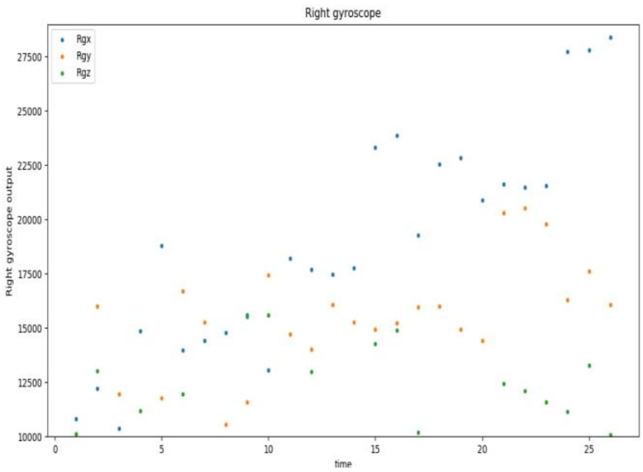
Fig(a)



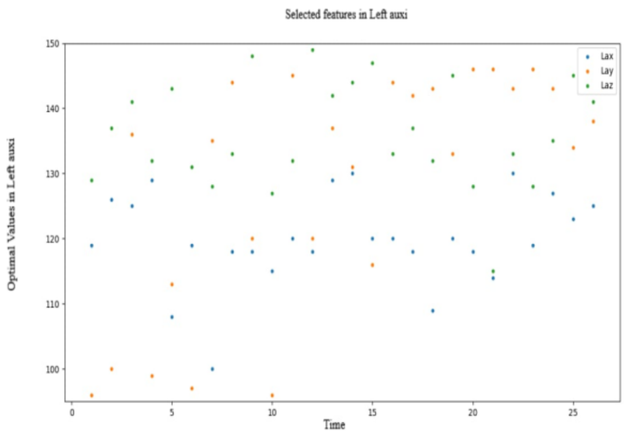
Fig(b)

Fig.4.(a &b). results in Left and

Feature Extraction right gyroscope



Fig(c)



Fig(d)

Fig.5.(c & d)Feature Extraction results in right and left accelerometer

Then cross validation is done for each feature subset. Based on the calculation each subset is assigned a weight and the best subset is chosen. Filter methods use general measurements metrics for weighing the feature. The embedded methods perform the feature set selection in conjunction with the model construction.

In our work, the digital data of gestures is obtained from the hyper terminal of the hardware module. The gestures are subjected to Min –max scaling method which is used for approving the gestures with respect to amplitude variations. The amplitude variations of inertial sensors is compared with a threshold value. The amplitude values above the threshold is termed as approved gestures and those that falls below the threshold are considered as useless gesture. Feature extraction results using Min –max scaling method of left and right gyroscopes and left and right accelerometers are shown in figure.4 and figure.5 respectively.

When each subject starts to perform the gesture, the amplitude of the sensors begins to vary from lower level to higher level. We monitor the variation of the digital data with respect to the gesture. When each subject performs the gestures repeatedly the values are noted manually, from that the optimal range of the data is found. That optimal range of the data is considered as selected feature. We have different value of optimal range for accelerometer and gyroscope. Among 204 features, 102 features are selected with respect to the optimal range of the data set. Based upon this range, graph for accelerometer and gyroscope is plotted and is shown in the above results figure.4 & figure.5 .Figure 4 shows extracted feature values of left and right gyroscope. g_x, g_y, g_z are the gyroscope values along x ,y and z axis respectively. Figure 5 shows the selected feature values of accelerometer and a_x, a_y, a_z indicates the accelerometer values along the x, y and z axis. Accuracy of the gesture depends on the best feature. From the obtained values, set of approved gesture is chosen by means of feature extraction. The average value of the approved gestures along the 3 axes inertial sensors reflects the hand orientation of the static and dynamic gestures. With the hand orientation data we form three clusters from the approved gesture sets. In this work we initiate improved K means grouping algorithm for assembling the clusters. We use distance probability classifier technique for finding the accuracy of the gestures

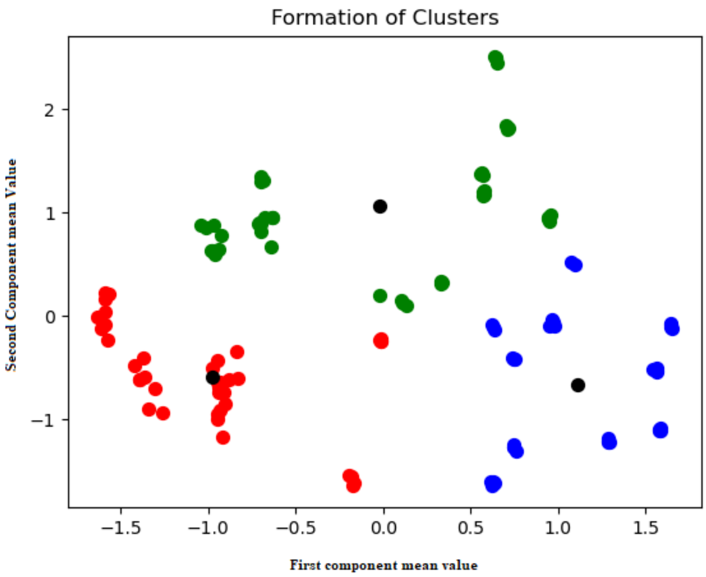


Fig.6.Cluster graph after applying improved k-means algorithm

4.2. Improved K-means algorithm

K–means algorithm can be done without any supervision. It is recognized for its plainness and its ability to solve clustering inconvenience. Here we establish a well improved form of k means algorithm. The main initiative behind k means algorithm is to obtain k centroids where each cluster denotes a class of related hand orientation. In this approach we assign the number of centroids as k= 3 for the hand orientation classifier. For developing clusters, a random hand orientation classification of approved gestures is implemented. The centroids are positioned in a scheming manner. Different arrangement of centroids causes dissimilar results. The centroids are positioned at larger distance from each other. Once the centroids are positioned, each dot in the incoming gesture action is matched with its nearest centroid. First stage in this algorithm involves in matching all the points in the data set. After comparing all the points, centroids values are re-calculated. Now, the points in the data set are matched with their neighbouring centroid counterparts. This process is an iterative process and it continues till the centroids do not displace. For minimising the error an objective function used is given as

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \| x_i^{(j)} - c_j \|^2 \qquad (1)$$

Where, x_i is Data points , C_j is Clusters, J is Objective function

The algorithm is composed of following steps

1. K points are positioned in space where the objects are being clustered points denote the initial centroid groups.
2. Objects are allotted for the centroids that are closely related.
3. The positions of the k centrois is calculated again once the objects are allotted.

Repeat the steps 2 & 3 until the centroids cannot be relocated. Our approach offers high accuracy by reducing the dataset dimensionality using the mean value. Initially the gesture data has 12 components that include 6 components from gyroscope and 6 components from accelerometer. These 12 components are reduced to 2 components.As per this algorithms for static gesture initially

we set k=3 it means that the gesture data is separated equally into three different groups. By separating the dataset equally in the clusters produces high accuracy in recognition. The centroids are selected aimlessly and the process is repeated until the centroids cannot change its position.
Finally the 26 alphabets are separated in to three clusters using their distance. This is shown in figure 6.

Cluster 0 →(A,B,C,D,E,F,G,H,I) – 09

Cluster 1 →(K,M,N,O,R,S,X,Y,Z) – 09

Cluster 2 →(J,L,P,Q,T,U,V,W) – 08

The algorithm k-means is very efficient, The processing time of this algorithm is less [15]. Figure.6 shows that clustering graph after applying improved k-means clustering algorithm. For sub words recognition, initially we set two major clusters representing the two different orientation and four minor clusters denoting the phases of the gestures. With cluster formation the observed data is separated.

4.3 Classification Results

In this approach, the distance probability classifier is introduced to measure the minimum distance. With the measured minimum distance, the gestures are classified. Classifying the gestures makes the accuracy of recognition more simple. The classifier is trained and tested with data from the same subject.

The data set includes 26 Alphabets and 2 sub words. Alphabets gestures are considered as static and sub-words gestures are considered as dynamic . The first step involves in capturing the gesture action using the accelerometer and gyroscope. From the hardware we obtain the digital data, then it is exposed to improved k-means algorithm in the classifier and the recognized gesture accurateness is evaluated.

After feature extraction 108 features are selected for alphabets and 21 features are selected for subwords from every subject. Among the 108 features of alphabets and 21 features of sub words, 80% of features is considered as training data and 20% of features is considered as testing data. Using training data the classifier is trained initially; once the classifier is trained using the testing data the accuracy is found. In this paper, we involve in concentrating on offline testing data. The accuracy for every alphabet is found separately. Various subjects are involved in gesture action, therefore various hand shapes and orientations are obtained. Overall accuracy is calculated by mean value of individual accuracies.

Classification of dynamic gestures is difficult compared with the static gesture. Because each dynamic gesture has different phase. In this work we use two sub words and each subword contains four phases namely the starting phase , gesture-1, gesture-2 and the ending phase with respect to the different subwords. These phases vary ,so the recognition of subwords is a challenging task.

The overall accuracy obtained in our approach is 96.55% for static gesture and 74.6% for dynamic gesture. Table.1. Shows the recognition accuracy of alphabets A to F by each subject. Similarly Table.2 shows the recognition accuracy for alphabets G to Z. The recognition accuracy for Two sub words performed by three different subjects shown in Table.3

Table.1. Recognition results of across 8 subjects (A to F)

	A	B	C	D	E	F
Subject 1	**96.24**	**93.13**	**93.83**	**92.96**	**93.05**	**88.615**
Subject 2	**97.79**	**95.68**	**94.27**	**95.34**	**91.91**	**91.02**
Subject 3	**95.79**	**95.06**	**93.86**	**94.31**	**92.29**	**71.37**
Subject 4	**95.13**	**96.42**	**92.35**	**98.03**	**96.22**	**94.39**
Subject 5	**93.41**	**94.99**	**91.54**	**98.04**	**94.44**	**89.3**
Subject 6	**97.96**	**94.36**	**97.65**	**92.51**	**93.44**	**93.21**
Subject 7	**95.95**	**96.23**	**97.44**	**93.57**	**91.34**	**92.72**
Subject 8	**95.79**	**93.13**	**93.83**	**92.96**	**93.05**	**86.25**
Over all accuracy	**96.04**	**95.12**	**94.42**	**94.97**	**93.24**	**88.66**

Table.2. Recognition results of across 3 subjects (G to O)

	G	H	I	J	K	L	M	N	O
Subject 1	**95.75**	**97.7**	**95.97**	**98.43**	**98.12**	**95.49**	**99.06**	**99.15**	**99.15**
Subject 2	**95.06**	**98.37**	**96.35**	**94.25**	**98.19**	**98.28**	**98.04**	**99.26**	**98.37**
Subject 3	**87.13**	**96.19**	**96.19**	**96.16**	**95.26**	**92.29**	**97.63**	**99.23**	**96.19**
Over all accuracy	**92.65**	**97.42**	**96.17**	**96.28**	**97.19**	**95.35**	**98.24**	**99.21**	**97.9**

Table.3. Recognition results of across 3 subjects (P to Z)

	P	Q	R	S	T	U	V	W	X	Y	Z
Subject 1	**98.61**	**98.13**	**98.23**	**98.4**	**98.96**	**98.4**	**98.71**	**98.61**	**99.47**	**98.72**	**98.31**
Subject 2	**97.28**	**99.29**	**97.28**	**98.25**	**99.56**	**96.64**	**98.47**	**98.49**	**97.61**	**98.73**	**99.47**
Subject 3	**95.97**	**98.73**	**98.46**	**97.6**	**89.8**	**96.57**	**98.57**	**97.02**	**98.09**	**97.4**	**98.68**
Over all accuracy	**97.28**	**98.72**	**97.99**	**98.08**	**96.11**	**97.20**	**98.58**	**98.04**	**98.39**	**98.28**	**98.82**

Table.4.Recognition results of across 3 subjects (2 sub words)

	Monday	Tuesday
Subject 1	**80.9**	**82.28**
Subject 2	**74.2**	**80.67**
Subject 3	**62.4**	**78.44**
Over all accuracy	**72.5**	**80.46**

Figure.7.Shows that the Classification results for the static gesture from A to F. First we experiment with static gestures from A to F as a result 8 observed data is captured from 8 subjects, improved k-means algorithm is used for classification and the overall recognition accuracy obtained from (A to F) is 93.74% in off-line testing .Figure.8. Shows the classification results for the static gestures (G to Z). the observed gestures from G to Z is experimented , now 3 observed data is captured from 8 subjects. Comparing with previous case this time we have fewer features set for training. The same algorithm used here for classification, the overall recognition accuracy from G to Z is 97.77%.

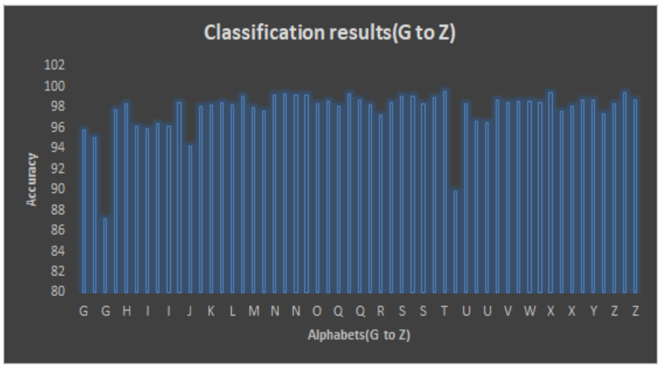


Figure.7.Classification results for the static gesture(A to F)

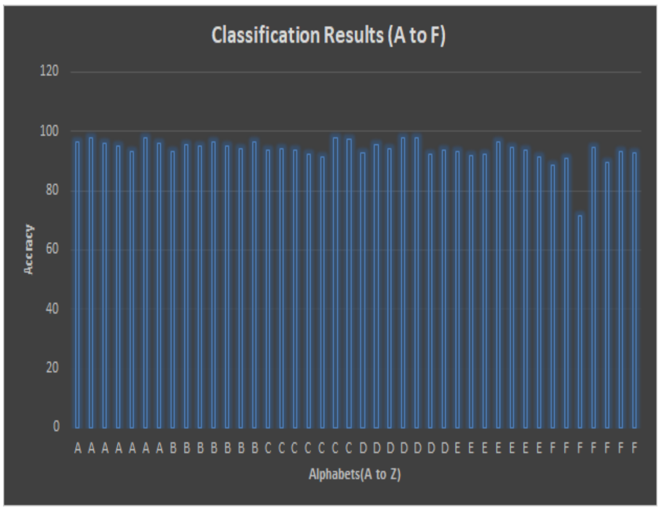


Figure.8.Classification results for the static gesture (G to Z)

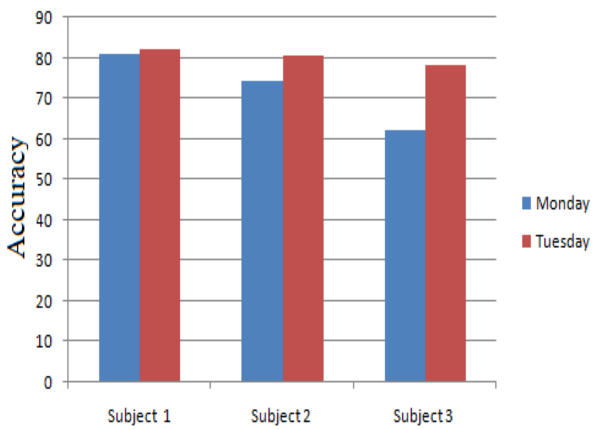


Figure.9.Overall Accuracy from (A to Z)

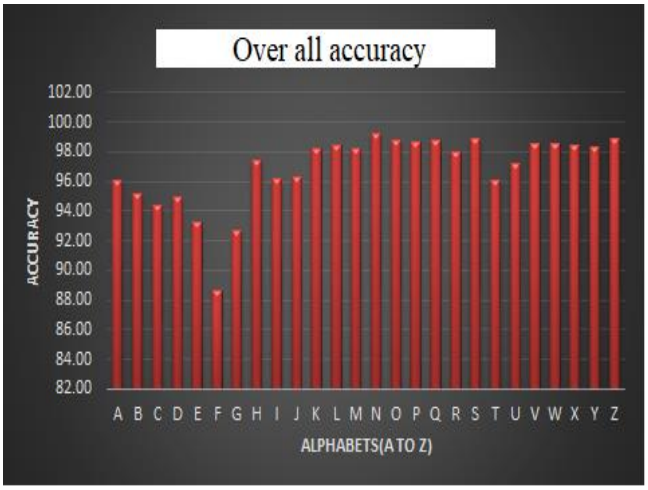


Figure.10.Classification results for the subwords

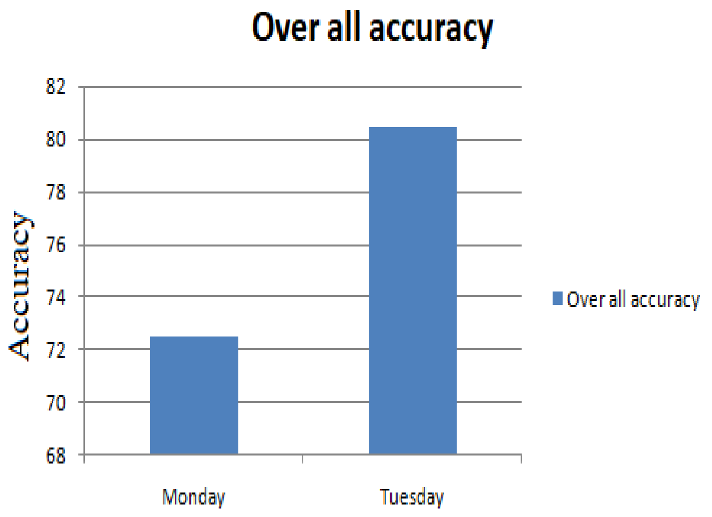


Figure.11. Subwords overall accuracy

Figure.9.Shows the overall recognition accuracies from (A to Z). The over-all static gesture accuracy obtained is 95.75%. Apart from that two sub-words which are the dynamic gestures are also tested. Capturing dynamic gesture is very difficult because the gesturing action is continuously moving in case of dynamic. Four-phases for every gesture is considered namely the start point, action 1, action 2 and the endpoint. With these four phases, the accuracy of dynamic gestures is obtained. The improved k-means algorithm is used for classification and the overall accuracy obtained for two sub-words is 76.48% is revealed in figure.10 and figure.11

5. CONCLUSION

This paper explored the first study of ISL recognition fusing gyroscope and accelerometer with hardware module. Experimental results on the classification of 26 ISL Alphabets and 2 ISL Sub words show that the proposed framework is effective to merge accelerometer and gyroscope information, with the average accuracies of 96.55% for ISL alphabets and 76.48% for two ISL sub words. Improved k-means algorithm is used to obtain the accuracies. As per our study it is concluded that the static gestures are recognized effectively by the hand orientation and improved k-means classifier than the continuous gestures. The accuracies for eight different subjects are achieved by testing offline data.

6. FUTURE SCOPE

This study explored 26 alphabets and 2 sub-words in Indian sign language. High accuracy is achieved for static gestures and this work is continued for improving dynamic gestures accuracy with more number of subjects.

List of Abbreviations:

SLR – Sign Language Recognition
ISL – Indian Sign Language
IMU – Inertial Measurement Unit

Conflict of Interest: It has been verified by the authors that there are no notable conflicts of interest for publishing this paper.

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REFERENCES

1. P.SubhaRajam,G.Balakrishnan, "Recognition of Tamil Sign Language Alphabet using Image Processing to aid Deaf-Dumb People".Procedia Engineering 30(2012)861-868.

2. Jian Wu et.al., "Wearable System for Recognizing American Sign Language in Real-Time Using IMU and Surface EMG Sensors".IEEE journal of Biomedical and Health informatics,Vol.20,No.5 September 2016.

3. Joyeeta Singha, et.al, "Recognition of Indian Sign Language using Live Video", Internaltional journal of computer application (0975-8887) Volume 70-No.19, May 2013.

4. T.Kuroda, et.al, "Consumer price data-glove for sign language recognition", proc.5th International conference, Disabilty, Virtual reality & association Tech. US 2000@2004|CDVRAT/university of Reading UK; SEN 0704911442, 2014.

5. V.K.Bairagi, et.al, "Glove based hand gesture Recognition Using ISL", International journal of latest trends in engineering and technology vol. (8) Issue (4-1) pp.131-137.

6. Robert Y.Wang, et.al, "Real-Time Hand-Tracking with a Color Glove", ACM transaction on Graphics, Vol.28, No.3, Article 63, 2009.

7. Ravikiran J, et.al , "Finger Detection for Sign language Recognition" , Proceedings of the International multi conference of engineers and computer scientists,Vol. 2,No.1,PP.234-520,2009.

8. Zhou Ren, et.al, "Robust Part-Based Hand Gesture Recognition Using Kinect Sensor", IEEE Transaction on Multimedia, Vol.15, No.5, 2013, pp: 1110- 1120

9. A.Y.Benbast and J.A.Paradiso, "An inertial measurement framework for gesture recognition and applications", in Gesture and sign language inhuman computer interaction.Newyork, NY, USA: Springer, 2002, pp.9-20.

10. O.Amft, H.Junker, and G.Troster, "Detection of eating and drinking arm gestures using inertial body-worn sensors," inProc.9th IEEE Int.Symp.wearable comput.2005, pp.160-163.

11. Y.Li, et.al, "A Sign Component-Based Framework for Chinese Sign Language Recognition Using Accelerometer and sEMG Data". IEEE Transaction on Biomedical Engineering, Vol.59, No.10, pp.2695-2704, October 2012.

12. I.Guyon and A.Elisseeeff, “An introduction to variable and feature selection.”J.Maxh.Learn.Res. Vol.3, pp.1157-1182, 2003.
13. A.Rakhlin, A.Caponnetto, “Stability of k-means clustering”, Advances in neural information processing systems.Vol.12, MIT Press, Cambridge, MA 2007. pp.216-222
14. A.K.Jain, R.C Dubes, “Algorithms for clustering Data”, prentice Hall Inc, Englewood Cliffs.NJ, 1988, ISBN 0-13-022278-X.
15. T.Velmurugan, “Peformance based analysis between k-means and Fuzzy C-means clustering algorithms for connection oriented telecommunication data. Elsevier, Applied soft computing 19(214) 134-146.
16. Jakub Galka et.al , “ Inertial motion sensing Glove for Sign language Gesture Acquisition and Recognition” , IEEE Sensors Journal , Vol.16.No.16, August 15, 2016, pp:6310- 6316
17. Zhiyuan et.al , “A Hand Gesture Recognition Framework and Wearable Gesture – Based Interaction Prototype For mobile devices” , IEEE Transaction on Human-Machine Systems , Vol.44, No.2 ,April 2014 ,pp:293-299
18. Celal Savur , Ferat Sahin , “ Real Time American Sign Language Recognition System by Using Surface EMG Signal” , IEEE 14th International conference on Machine Learning and Applications,2014,.
19. Kyle Van Volkinberg and Gregory Washington, “Development of a Wearable Controller for Gesture-Recognition-Based Applications Using Polyvinylidene Fluoride”, IEEE Transaction on Biomedical circuits and systems, 2017,pp:1-10.
20. Kehuang et.al, “ Sign Transition Modeling and a Scalable Solution to Continuous Sign Language Recognition for Real-World Applications”,ACM Transaction on Accessible Computing ,Vol.8,No.2,Article.7,January 2016 ,pp: 7 – 7:23.
21. Lim Wei Howe et.al, “Comparison of Hand Segmentation Methodologies for Hand Gesture Recognition”, IEEE Conference, 2008.
22. V. Mallikalava, S. Yuvaraj, K. Vengatesan, A. Kumar, S. Punjabi and S. Samee, "Theft Vehicle Detection Using Image Processing integrated Digital Signature Based ECU," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2020, pp. 913-918
23. S Yarisha Heera et.al , “ Talking Hands – An Indian Sign Language to Speech Translating Gloves”, International Conference on Innovative Mechanism for Industry Applications, 2017.
24. Purva.A.Nanivadekar et.al, “Indian Sign language Recognition: Database Creation, Hand Tracking and Segmentation”, International conference on Circuits, Systems, Communication and Information Technology Application, 2014.
25. Jong-Sung Kim et.al , “A Dynamic Gesture recognition System for the Korean Sign Language(KSL)”, IEEE Transaction On Systems, Man , Cybernetics – Part B : Cybernatics,Vol.26, No.2 , April 1996.
26. Johanna Mesch et.al, “Manual backchannel responses in signers’ Conversation in Swedish Sign Language”, Language and communication 50(2016),pp:22-41
27. Wun-Guang Liou et.al, “Trajectory-Based Sign Language Recognition Using Discriminant Analysis in Higher-Dimensional Feature Space”, IEEE, 2011

28. K. Srinivas, g. Madhukar rao, k. Vengatesan, p. Shivkumar tanesh, a. Kumar,and s. Yuvaraj,"an implementation of subsidy prediction system using machine learning logistical regression algorithm",advances in mathematics: scientific journal 9 (2020), no.6, 3407–3415

29. Shihab Shahriar Hazari et.al, “Designing a Sign Language Translation System using Kinect Motion Sensor Device”, International conference on Electrical , computer and communication Engineering,2017.

30. Muhammad Asad et.al , “Kinect Depth Stream preprocessing for Hand Gesture Recognition”,IEEE,2013,pp:3735-3739.

31. Yongjing Liu et.al, “Image Processing and Recognition of Multiple Static Hand Gestures for Human – Computer Interaction”, Seventh International Conference on Image and Graphics, 2013.

32. Chenyang Zhan et.al , “Histogram of 3D Facets:A Characteristic Descriptor for Hand Gesture Recognition”, International Conference on Automatic Face and Gesture Recogniton ,2013.

33. Jeroen et.al, “Sign Language Recognition by Combining Statistical DTW and Independent Classification”, IEEE Transaction on pattern Analysis and Machine Intelligence, Vol.30, No.11, November 2008, pp: 2040 -2046.

34. Javier Jimenez et.al, “Mexican Sign Language Alphanumerical Gestures Recognition Using 3D Haar-like Features” , IEEE Latin America Transaction , Vol.15 issue.10,2017, pp:2000-2005

35. Cihat et.al, “Building machine-readable knowledge representations for Turkish sign language generation”, Knowledge based systems, Vol.108, 2016, pp: 179-194.

36. Ala addin et.al, “Transform-based Arabic Sign Language recognition”, Procedia Computer Science, Vol.117, 2017, pp: 2 – 9.

37. M.Mohendes et.al, “Image-Based and Sensor –Based Approaches to Arabic Sign Language Recognition”, IEEE Transaction on Human-Machine Systems, Vol.44, Issue.4, 2014, pp: 551-557.

38. VengatesanK, E Saravana Kumar, S. Yuvaraj, Punjabi Shivkumar Tanesh, Abhishek Kumar. (2020). An Approach for Remove Missing Values in Numerical and Categorical Values Using Two Way Table Marginal Joint Probability. International Journal of Advanced Science and Technology, 29(05), 2745 - 2756