**Literature Review:**

**1] Machine Recognition of Auslan Signs Using Power Gloves towards Large Lexicon Recognition of Sign language.**

Instrumented gloves use a variety of sensors to provide information about the users’ hands. They can be used for recognition of gestures especially well-defined gestures sets such as sign language. However recognizing gestures is difficult task, due to intrapersonal and interpersonal variation is performing them. One approach to solving this problem is to use Machine learning. In this paper, **sample of 95 discrete Australian Sign Language signs were collected using a Power Gloves**. Two machine learning techniques were applied **instance based learning and decision tree learning** to the data after some single features were extracted. Accuracy of **approximately 80 percentages was** achieved **using IBL** despite the server limitation of the glove.

The data extracted from glove are concise and accurate compared with the information from a video camera. There are also several technical problems which need to resolved, such as automatic calibration of gloves and handling of noise.

Instance base learning also known as 1 nearest neighbor, works by storing all the training instances in attribute space. Give a test instance, it finds the closest instance in the attribute space and classifies the test instance according to this nearest neighbor. They might look at the five nearest instances and use a vote technique.

Decision tree building works by building a hierarchy of decisions based on attribute values. For these experiments they used C4.5 as the decision tree builder.

Algorithm were tested using 5 fold cross validation. That means that data collected was spilt into 5 equally sized sets. Each time one set was used as the test set and the remained as training. This was done with each of the sets and results averaged.

The bounding box of sing is the box in space in which the test sing fits. The bounding box can be represented as 2 vectors : the coordinate of the bottom left hand near corner of the box and the coordinate of the right hand far corner of the box. The results of using bounding boxes are good. They provide accuracy of approximately 30 percent of the both C4.5 and IBL.

**Histograms:**

1] x,y and z position : IBL approximately 25 per cent accuracy was obtained and with C4.5 they did worse with approximately 15 per cent accuracy .

2] Wrist rotation and finger bend: Achieving accuracies of 40 per cent with IBL and 30 per cent with C4.5.

**Time Division :**

In this technique is to segment the sign into fixed number of equally sized segments and then calculate the average values of x,y and z position ,wrist rotation and finger bend for each segment. If too many segment they will be extremely sensitive to variation in this time and noise. With IBL accuracy as approximately 65 per cent and with C4.5 the accuracy was approximately 40 per cent. It was empirically found that five segments led to the best results.

**Synthesis:**

Using the best attribute to an accuracy of approximately 80 per cent for the three large samples collecting using IBL. For the other person with 6 training samples accuracy was 58.5 per cent. Performance with decision tree builder was significantly worse than with IBL. Considering the capabilities of the glove and size of the lexicon the investigator believes the results are very promising.

2] Gesture Recognition and Machine Learning Applied to Sign Language Translation

In this paper we propose an intelligent system for translating sign language into text. This approach consists of hardware and software. The hardware is formed **by flex, contact, and inertial sensors mounted on a polyester-nylon glove**. The software consists of a classification algorithm based on the **k-nearest neighbors, decision trees, and the dynamic time warping algorithms**

The proposed system was tested at **translating 61 letters**, **numbers, and words from the Ecuadorian sign language**. Experimental results demonstrate that our system has a **classification accuracy of 91.55%.**

The dynamic time warping (DTW) algorithm is used for a pattern recognition task. This system is able to identify 52 static and dynamic gestures. Since these approaches are based on artificial vision systems, their performance is highly dependent on the light conditions where the system is used. In [8], the sign language translation is based on a sensor called leap motion controller. This approach uses decision trees (DT) and genetic algorithms to recognize 24 static characters with 82.7% of classification accuracy

The hardware is composed of 3 types of sensors**: flex, contact, and inertial**. Combining the information of these sensors, we estimated the relative orientation and movement of the hand and its fingers. These estimates are used as the inputs of a gesture recognition system .The hardware is composed of 3 types of sensors: flex, contact, and inertial. Combining the information of these sensors, we estimated the relative orientation and movement of the hand and its fingers. These estimates are used as the inputs of a gesture recognition system

**Method**

*Types of hand movements*

These authors studied the following 4 types of movements of the hand: flexion and extension of the fingers, flexion and extension of the wrist, supination and pronation of the forearm, and radial and ulnar deviation of the hand.

*Description of the Developed Hardware*

All the sensors used in this work were mounted on a polyester-nylon glove and their distribution is according to the graph that is shown in Fig. 3. The flexion and extension signals of the fingers were acquired using flex sensors. Two flex sensors were attached to each finger, except in the case of the thumb where we used only one sensor. We used two flex sensors because the two phalanges are needed for representing the movement of a finger.

3] Applying tee line shorthand Using leap motion controller By Weikai Zang

A hand gesture recognition program was developed to recognize users’ **Teeline** shorthand gestures as English letters, words and sentences using **Leap Motion Controller**. The program is intended to provide **a novel way** for the users to interact with electronics by waving gestures in the air to input texts instead of using keyboards. In the recognition mode, the dynamic time **warping algorithm** is used to compare the similarities between different templates and gesture inputs and summarize the recognition results; in the edit process, users are able to build their **own gestures to customize the commands**. A series of experiment results show that the program can achieve considerable recognition accuracy, and it had consistent performance in face of different user groups.

The goal of this thesis is to **design a** **program using the hand motion-sensing feature of the Leap Motion controller to detect people’s writing gestures in the air and recognize them as plain texts in English**.

Machine Learning is the most commonly used gesture recognition method. **Hidden Markov Model (HMM) and Dynamic Time Warping (DTW)**, two kinds of machine learning methods, are widely applied in speech recognition systems.

**Hidden Markov Model is a statistical analysis model** that can be used to **describe the temporal and spatial variations** of gesture signals. When applied to fingertip tracking

**Dynamic Time Warping is an algorithm** for **measuring similarity between two temporal sequences even though the lengths of the two sequences are different.**

The main objective of this thesis is to develop a program that employs the **DTW algorithm to analyze and recognize three-dimensional writing gestures using Leap Motion controller**. The LM is able to detect and record hands’ and fingers’ movements in the air, and an abbreviated **symbolic writing method called Teeline shorthand** will be employed as writing inputs. The program will perform the

The hand gesture recognition algorithms can be divided into **three main categories**: **template matching-based algorithms, statistics-based algorithms, and data classification-based algorithms**. Dynamic Time Warping (DTW) is a well-known template matching technique with the **advantages of simple principle and flexible operation.**

**Euclidean distance is an efficient method** for calculating the distance between two sequences with same length; however, in many cases, there are possibilities where the lengths of two time-series are unequal.

Data input by the user, **the Leap Motion controller that tracks and records hand movements**, the **display window that shows the movement path**, the **console window that receives commands and gives output**, and the **database that stores templates** for the matching algorithm.

In Recognition Mode, only one output is allowed: the **recognition result analyzed by the program using the Dynamic Time Warping algorithm**. In order to deliver a clear explanation, the program’s work process in

The program in this project applied a machine learning method called Dynamic Time Warping (DTW) to implement the recognition capability. There were two modes built in this program: Recognition Mode (RM) and Edit Mode (EM). The RM is the main function performed by the program, in which users drew Teeline shorthand gestures using their fingers or hands, and those gestures were recognized as English letters, words and sentences by the program.

In order to test the program’s performance, specifically the recognition accuracy, a series of experiments were conducted using two different databases. One database was built byan experienced user of using motion control devices and Teeline shorthand, and the other database was built by novices. All the other properties of the two databases were the same. The experiment results were analyzed in SPSS using different means, such as T test and ANOVA, and the analysis revealed the following findings:

The recognition accuracy of the program has a direct relationship with the sample size in the database to some extent, and there are optimal sample sizes for each Teeline characters in two databases at which further increases in sample size doesn’t leas to big increases in recognition accuracy.

appropriate for the program to achieve high recognition accuracy.

The program’s recognition accuracy is uniform for users in different age ranges, gender, handedness and experience with video games and motion control devices.