A Brief Study on Sign Language Recognition System

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ABSTRACT: ***Because of its capacity to bridge the gap between deaf and hearing individuals, the Sign Language Recognition System (SLR) is widely sought for. Due of many difficulties, a powerful SLR is still unattainable in the actual world. Furthermore, as we all know, the identification of sign languages has become one of the most significant study topics in the realm of human-computer interaction (HCI). As a result, this paper provides an overview of the most important investigations based on the Sign Language recognition system, as well as a discussion of the created system, which is divided into sign capture methods and recognition approaches. By evoking significant issues connected with the established systems, the strengths and drawbacks that support the system working flawlessly or otherwise will be emphasized. Then, based on integrating EMG sensors with a data glove, a new approach for building SLR systems is presented. For assigning word boundaries for streams of words in continuous SLR, this technique uses electromyography signals collected from hand muscles. The suggested method is intended to address the issue of word segmentation, resulting in improved recognition capabilities for the continuous sign recognition system.***

KEYWORDS: ***Artificial Neural Network, Data-Glove, Hidden Markov Model, Posture, Sign Language Recognition System.***

1. INTRODUCTION

Instead of acoustic sound patterns, sign language physically communicates sign patterns utilizing hand forms, orientation and motions of the hands, arms, or torso, facial expressions, and lip patterns to convey word meanings. Around the globe, many sign languages exist, each with its unique vocabulary and motions[1]. ASL (American Sign Language), GSL (German Sign Language), BSL (British Sign Language), and others are examples. Interpreters, friends, and relatives of the deaf, as well as individuals, who are hard of hearing themselves, often utilize this language in deaf communities. However, outside of these groups, these languages are not widely spoken, resulting in communication obstacles between deaf and hearing individuals.

Sign language communication is multimodal, including both manual and non-manual signals in addition to hand movements (i.e. manual signing). In sign language, gestures are described as particular patterns or motions of the hands, face, or body used to convey feelings. However, only manual signing is addressed in this article[2]. A hand gesture is described as a result of posture in a temporal domain, while hand posture is defined as a particular form of hand flexion at an instantaneous moment. The term "gesture" is used in this article to refer to a hand gesture that is also referred to as a sign or a phrase.

Many works of research have been directed toward developing a sign recognition system for various sign languages over the last decade, and it has been concluded that such a system is challenging for various disciplines such as gesture capturing methods, machine learning classifiers, human action understanding, and natural language processing. Unfortunately, the majority of newly released sign recognition systems are designed as standalone systems, with each motion being supplied individually to be detected[3]. A continuous sign language recognition system is described as a system that converts a “stream” of gestures into intelligible speech or text. It's more intriguing than solitary since genuine human signals are constant, and any isolation would disrupt communication. The complexity of the sign recognition system stems from the fact that sign languages are the least similar, with large vocabularies and referential language, as opposed to voice languages, which include co-articulation of several human body signals, making the task of recognizing isolated or continuous signing extremely complex. Several methods to sign recognition have recently been suggested; nevertheless, the efficient recognition of automated sign language systems remains an unresolved issue.

1.1 Sign Capturing Method:

1.1.1 Leap Motion:

The Leap Motion controller is a sensor that recognises and transforms hand movement into computer commands. Two infrared cameras and three infrared LEDs make up the system. The LED emits an infrared light signal, while the camera records 300 frames per second of reflected data. These signals are sent to the computer via USB connection to be processed further. Figure 1 illustrates the Leap motion controller with USB.

Figure 1: Illustrates the leap motion controller with USB[4]

1.1.2 Vision-based sign extraction:

For the recognition of Sign Language, vision-based techniques are extensively used. Sign motions are recorded by a fixed camera in front of signers in these techniques. The retrieved pictures depict the fingers, palms, and face in terms of posture, position, and motion. Following that, each video frame must be processed to separate the signer's hands from other background objects in an image processing phase. The image extraction techniques have the benefit of recovering the signer's face and body movements; nevertheless, they are often linked with image noises supplied from a variety of sources (camera, light, color matching, and background). Some researchers have attempted to rebuild the damaged portions using an error filter, but the issue is that mistakes are related to a dynamic environment. Another problem with a real-time vision system is the massive processing required. Nielsen et al., for example, proposed a real-time vision system that utilizes a rapid segmentation technique to detect hand position with few data in order to speed up the identification process. However, this approach misses out on important hand characteristics, resulting in poor identification accuracy. Figure 2 illustrates the module of Vision based sign extraction.

Figure 2: Illustrates the module of Vision based sign Extraction[5]

1.1.3 Data-Glove:

Data-gloves are special gloves that have a strain gauge and a hand tracker built into them. Hand and finger bend are detected using a strain gauge sensor. The hand tracker is an electronic device that measures the position, orientation, velocity, and direction of a person's hand in relation to a fixed reference. The data-glove gesture interaction produces excellent results, particularly for sign capture in SLR with high reliability and no need for pre-processing. The major disadvantage of dataglove is that it requires the user to wear gloves, which may obstruct convenience and natural mobility. In this approach, non-manual motions are also ignored. Figure 3 shows the module of Data glove with sensors.

Figure 3: Illustrates the module of Data glove with sensors[6]

1.1.4 EMG (electromyography):

The electrical potential signal produced by muscle cells is measured and recorded using an electromyography (EMG) sensor, which uses differential pairs of surface electrodes to do so. Control commands for prosthetic limbs and virtual games have been successfully implemented using EMG. Because various motions correspond to distinct EMG muscle signatures, utilizing EMG data for gesture identification is feasible. EMG has recently shown promising results in hand pattern recognition utilizing EMG signals. Figure 4 shows the sample of EMG.

Figure 4: Illustrates the module of EMG for Sign Capturing[7]

1.2 Gusture Classfier:

1.2.1 Artificial neural network approach:

A connectionist method to computation is used to process data in an artificial neural network, which is made up of a linked set of artificial neurons. The effectiveness of neural networks in sign language recognition has been lauded by many academics. The neural network method's greatest benefit is its universality. It also represents the capacity to explicitly learn associations from modelled data while satisfying real-time recognition limitations. Different network models exist for training the neural net for ASR, with Back Propagation, Multilayer Perceptron (MLP), and Simple Recurrent Networks being the most popular (SRN-Elman and Jordan networks).

1.2.2 Hidden Markov Model:

Recognition of British sign language Data was acquired using an image method and a markov chain in conjunction with independent component analysis. The motion and form of hands were extracted using feature extraction. The Viterbi method was employed to verify the results. The multilayer architecture in sign language recognition, which employs a mix of DTW and HMM for signer-independent CSL recognition. The DTW/ISODATA methods are

used to solve the vocabulary space confusion set. The recognition accuracy was higher than that of the HMM-based system.

2. LITERATURE REVIEW

Manisha U. Kakde et al. discussed a review for Sign Language Recognition [8]. Communication between a deaf-mute and a hearing person has always been difficult. This article examines several approaches to lowering communication barriers by designing an assistive gadget for deaf-mute people. The progress of embedded systems allows for the creation and development of a sign language translation system to aid the deaf. There are a variety of assistant tools available. The major goal is to create a real-time integrated technology that will help physically challenged people communicate more effectively.

Mahesh Kumar N B discussed about conversion of Sign Language into Text [9]. One of the fastest-growing areas of study is sign language recognition. In this field, several innovative approaches have lately been created. Sign Language is mostly used by deaf and dumb people to communicate. This article uses MATLAB to demonstrate the recognition of 26 hand motions in Indian sign language. Pre-processing and hand segmentation, feature extraction, sign identification, and sign to text are among the four modules included in the proposed system. Segmentation may be done using image processing. Eigen values and Eigen vectors, which are utilised in recognition, are among the characteristics extracted. For gesture detection, the Linear Discriminant Analysis (LDA) algorithm was employed, and the identified gesture was translated into text and speech format. The suggested system aids in the reduction of dimensionality.

Lalit Goyal et al. discussed a review on text to sign translation System[10]. There are several machine translation systems for spoken languages, but there are few that translate between spoken and sign languages. Because Sign Language is a visual spatial language that utilizes hands, arms, face, head, and body postures for communication in three dimensions, the translation from Text to Sign Language differs from the translation between spoken languages. Because the grammatical rules for Sign Language are not established, translating from text to Sign Language is difficult. Still, a variety of methods for translating Text to Sign Language have been utilized, with the input being text and the output being pre-recorded films or computer-generated animated characters (Avatar). The study on automated translation from text to sign language is reviewed in this article.

3. DISCUSSION

Sign Language Recognition is a game-changer for deaf-mute individuals, and it's been studied for years. Unfortunately, each study has its own set of constraints and is still not economically viable. The techniques utilized to create Sign Language Recognition differ from one researcher to the next. Sign Language Recognition system is very helpful for the people who are deaf and cannot talk. This paper discusses about Sign language recognition system, sign capturing method for sign language recognition system and gesture classifier like Artificial Neural Network and Hidden Markov Model for sign system. The suggested method is intended to address the issue of word segmentation, resulting in improved recognition capabilities for the continuous sign recognition system. The future of this sign language recognition system is bright as it will be helpful for elderly people and those people who are deaf.

4. CONCLUSION

In contact with the deaf community, a constant sign language recognition system is very desired. The most common techniques for recording hand movements in sign language are image-based and hand glove-based approaches combined with a hand tracker. Data-gloves allow for more complex movements including individual fingers, wrists, and hands, resulting in more flexible, accurate, and reliable gesture detection. The image-based approach, on the other hand, allows for user-independent feature extraction while requiring additional processing for feature extraction and noise reduction. It, on the other hand, communicates facial and body motions, allowing for more complex sign gestures. Because they did not saturate or get trapped in oscillatory patterns, ANN neural networks displayed resilient behavior during gesture prediction. The disadvantage of employing ANN classifiers is the time and effort necessary to train them, as well as the time and effort required to expand new vocabulary. Because of its capacity to model words based on sets of preset states, the Hidden Markov Model (HMM) classifier is also useful in sign recognition. However, it has a drawback in that it is predicated on the assumption that the distribution of individual observations can be represented by a combination of Gaussian densities, which is not necessarily the

case. In sign language, HMM has been found to offer worse discriminating than neural networks when compared to HMM and ANN, which is still a point of contention.

Because the majority of the recognition results presented are based on the author's own data and vocabulary, the results will not accurately represent the dependability of these systems. Rather than reporting the correctness of tested words, it seems to be more interesting to establish performance metrics in sign recognition systems. Furthermore, since genuine human gestures are continuous, adding a stand-alone system may substantially interrupt the natural flow of human contact, and thus has less utility in the real world of sign identification. A completely automated sign recognition system's success hinges on resolving existing issues with continuous gesture recognition. Unfortunately, the proposed solutions are based on an underlying assumption that may fulfill a predetermined condition or a set of motions in a particular sign language. Another unpractical technique requires the signer to hold a contact switch while executing the signs. As previously stated, it has been shown that creating a continuous recognition system for a big vocabulary is difficult if the input stream is not artificially divided.

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