

Gesture Language Recognition

Divya Kale¹, Bhagyashri Patle², Jividha Nandanwar³, Kaushik Uchibagle⁴, Rahul Bhandekar⁵

^{1,2,3,4}Students, ⁵Assistant Professor
Wainganga College of Engineering and Management, Nagpur, India, 441114

divyakale31@gmail.com

Received on: 01 April,2023

Revised on: 24 April,2023

Published on: 26 April,2023

Abstract –One of the non-verbal communication methods adopted in gesture language is hand gestures. It is mostly used by deaf and dumb individuals to communicate with other people or among themselves when they have hearing or speech issues. Many producers across the world have created numerous gesture language systems; however, they are neither adaptable nor economical for end users. As a result, the program shows a system prototype that can automatically detect gesture language to aid deaf and dumb individuals to communicate more efficiently with each other and other people. Normal people often find it difficult to comprehend and converse with dumb individuals, hence they are typically denied regular social interaction. Long-term research has led to a breakthrough in aiding deaf-mute people: gesture language recognition. Every study, sadly, has constraints that prevent it from being applied economically. Some studies have been proven to be effective in understanding gesture language, but they cost a lot of money to market. Researchers are receiving increasing attention these days for creating commercially viable Gesture Language Recognition. Research is conducted in a variety of methods. It begins with the data collection techniques. The cost of a suitable device necessitates a variety of data-collecting techniques; nonetheless, a low-cost technique is required for the commercialization of the Gesture Language Recognition System. Additionally, academics' approaches to creating Gesture Language Recognition differ.

Keywords-Communication, hand gestures, gesture language, Artificial Neural Network (ANN), convolution neural network (CNN)

I- INTRODUCTION

In gesture language, meaning is expressed visually through facial expressions, hand gestures, and body language. People who have trouble hearing or speaking might benefit greatly from learning gesture language. The process of turning these gestures into words or alphabets of officially recognized spoken languages is known as gesture language recognition. As a result, an algorithm or model that converts gesture language into words can aid in closing the communication gap between those who have hearing or speech difficulties and the rest of society. Computer vision and machine learning researchers are now working on the identification of hand gestures based on vision. To simpler and more natural without the additional devices, is an area where many academics are researching. Therefore, the main objective of research on gesture recognition is to develop systems that can recognize human gestures and use them, for instance, to communicate information. Vision-based hand gesture interfaces need quick and incredibly reliable hand detection as well as real-time gesture recognition for this to work. In this context, gesture language recognition, the means of communication used by the deaf, is a strong human communication modality with many potential uses. Computer vision and machine learning researchers are actively investigating hand gesture detection for human-computer interaction. Making systems that can recognize certain gestures

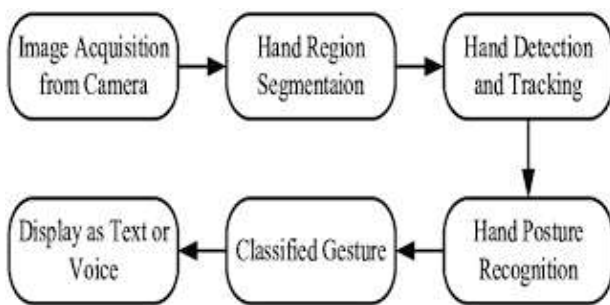
and utilize them to transmit information or control devices is one of its main objectives. However, hand postures are the static structure of the hand, but gestures are the dynamic movement of the hand, and gestures need to be described in the spatial and temporal domains. The two main methods used to recognize vision-based methods and data glove methods. The primary objective of this endeavor is to develop a vision-based system capable of real-time gesture language recognition. The rationale behind opting for a vision-based system is that it offers an easier and more natural means of communication between a person and a computer. Because the human hand is one of the most gesture means of communication in daily life, research on human-machine interaction through gesture recognition has led to the use of such technology in a wide range of applications, including touch screens, gaming consoles, virtual reality, medical applications, and gesture language recognition. The most natural means of communication for deaf individuals is gesture language, although it has been noted that they have trouble interacting with hearing people.

II -METHODOLOGY

The objective of this research project is to Static or dynamic hand gesture detection for real-time systems involving human-computer interaction is a difficult job that is now the subject of ongoing study. Numerous works on gesture recognition and well-presented methodology can be found in [5, 6]. Careful hand feature selection and extraction are crucial factors to consider in computer vision applications for hand gesture identification and classification for real-time human-computer interaction, as stated in the preceding section. This process is essential to determining if a particular hands shape fits a certain model in the future or which representative class is the most comparable. Wacs [7] asserts that the success or failure of any ongoing or future effort in the field of human-computer interaction utilizing hand gestures depends on the right feature selection and its application with advanced learning and recognition algorithms. In his paper [8], Trigueiros offered a comparison of seven alternative hand feature extraction algorithms to classify static hand gestures. The findings indicated that the radial gesture and centroid distance were the characteristics that, when utilized superior outcomes while being relatively low-complexity in terms of computing. He

has also used a vision-based system [9] that just requires a few finger instructions to operate a wheelchair. The system recognizes the user's hand, extracts the user's fingertips, and uses these properties to create user instructions for wheelchair control. In-plane rotation invariant, and scale inscape-invariant identification were all accomplished by Wang [10] using the discrete Adaboost learning method combined with SIFT features. Conceal [Conseilmined Humoments and Fourier descriptors as two alternative form descriptors for the identification of 11 hand postures using a vision-based method. They came concluded Fourier descriptors offer higher recognition rates than Hu moments. On a database of American Gesture Language, Barczak [12] compared the performance of Fourier descriptors and geometric moment invariants. The findings indicated that some classes in the database cannot be distinguished by either descriptor. In a reasonable balance between identification accuracy and computational burden for a real-time application, Bourennane [13] provided a shape descriptor comparison for hand posture detection from video. Two families of contour-based Fourier descriptors and two sets of region-based moments, all of which are invariant to hand translation, rotation, and scale changes, are the subjects of their studies. They assert that they conducted thorough testing on the Triesch benchmark database [14] and independently under more practical circumstances. The study's overall findings demonstrated that the k-nearest neighbor combination with common set Fourier descriptors had the greatest recognition rate, reaching 100% in the learning set and 88% in the test set. On extremely low-resolution photos, Huynh [15] gives an evaluation of the SIFT Color SIFT, and SURF speeded-up descriptors. Using ground truth accurate matching data, the performance of the three descriptors is compared to one another on the accuracy and recall metrics. The findings of his experiments revealed that while SURF is superior to SIFT under changes in light and blurring, both SIFT and color SIFT are more resilient under changes in viewing angle and viewing distance. The SURF descriptors present themselves as a good substitute for SIFT and CSIFT in terms of calculation time. Fang [16] introduced a hand posture identification method with what they dubbed a co-training technique [17] to handle the issues of a high number of labeled often expensive time spent on training, conversion or normalization of features into a single feature space, and other issues. The basic goal is to

train two distinct classifiers alongside one another outdoors on unlabeled examples. They assert that their strategy enhances recognition performance in a semisupervised manner with less labeled data. The centroid distance Fourier descriptors were employed by Ravi [18] as hand-shape descriptors of gesture language. According to their test findings, the Manhattan distance-based classifier and Fourier descriptors were able to obtain identification rates of 95% with little computational delay. Machine learning algorithms have been successfully used in many research fields to perform classification and learning tasks, including facerecognition and facial expressions [19, 20], automatic musical gesture recognition by a computer [21], classification of robotic soccer formations [22], human physical activity from on-body accelerometers [23], automatic road-gesture detection [24, 25], static hand gesture classification [26], and serious games applied to serious problems [27, 28]. Four machine learning techniques have been compared by Trigueiros [26] using two datasets of hand attributes. The datasets used in their investigation included a variety of hand traits. digested real-time hand gesture detection system for human-robot interface using a Support Vector Machine (SVM).



III - CONCLUSION

Normal people have trouble understanding the hand gestures used by deaf individuals because they use them to communicate. Therefore, there is a need for systems that can identify various indications and communicate information to regular people. It's important to interact with everyone in our modern culture, whether it's for fun or for the worker a being needs to communicate. However, individuals with speech or hearing impairments require a different form of communication than vocalization. They use gesture language as a means of communication. However, learning and understanding gesture language takes a lot of practice, and not

everyone will comprehend what the movements in gesture language indicate. Furthermore, learning gesture language takes time because there is no reliable, portable instrument for doing so. Hearing or speech-impaired individuals who are proficient in gesture language need a translator who is equally proficient in gesture language to effectively communicate their ideas to others. This technique assists persons with hearing loss or speech impairments in learning and translating their gesture language in order issues. These gesture languages may be divided into two categories: static gesture and dynamic gesture. The dynamic gesture is utilized for specific concepts, whereas the static gesture is used to symbolize the alphabet and numbers. Additionally, dynamic encompasses phrases, clauses, etc. The difference between static and dynamic lies in the movements of the hands, the head, or both. The three main elements of gesture language-finger spelling, word-level vocabulary, and non-manual features-make it a visual language. Instead of using keywords, finger spell words letter by letter and deliver the idea. Nevertheless, despite numerous research efforts over the last few decades, the language translation is rather difficult. To create a software system capable of recognizing ISL hand gestures in real time using deep learning methods. The goal of this research is to foresee the ISL system's "alphanumeric" gesture. Automated gesture language analysis is essential to enabling communication across the visually impaired, Deaf, and hearing populations and to bridging the access gap to future-generation Human-Computer Interfaces. To transmit meaning, three-dimensional locations, hand gestures, and other body parts are employed. Its vocabulary and grammar are entirely distinct from those of spoken and written languages. To transmit meaningful information, spoken language. Being unable to hear the system makes it difficult for dumb and deaf individuals to communicate with it at work. It is also risky for them to travel places alone since they cannot hear cars, bikes, or other people approaching.



IV- ACKNOWLEDGMENT

A system for identifying solely static gestures and alphabets has evolved into one that can correctly identify dynamic motions that appear in continuous sequences of pictures. Today's researchers are concentrating more on creating a broad vocabulary for gesture language recognition systems. Many academics are employing a limited vocabulary and their databases to create their own Gesture Language Recognition Systems. For several of the nations participating in creating gesture language recognition systems, a large database that was built is still not available. In particular, the Kinect-based information, which offers the color stream and depth stream video. Researchers use a variety of categorization methods when figuring out what gesture language is being used. The comparison of one approach to another method for the Gesture Language Recognition System is still based on the individual's preferences and constraints. Because gesture language varies among nations and because each researcher sets their limitations, it is difficult to compare methodologies fairly and directly. The majority of the country has several gesture languages based on their grammar and how they convey each phrase, such as by word or by sentence. We conclude that classification techniques for gesture language recognition can be employed with SVM+HoG and convolutional neural networks. However, to demonstrate an improvement in accuracy, pre-training must be carried out with a bigger dataset. We were able to surpass the accuracy reported in earlier literature by 71.88% using SVM+HoG for the ISL dataset utilizing depth pictures dataset when 4 subjects were utilized for training and a separate subject for testing.

REFERENCES

- [1] *Cambridge Dictionary*. [Online]. Press CU; 2017. <http://dictionary.cambridge.org/dictionary/english/deaf>
- [2] Chen X., Zhou Y., Wang H., Chai X. Low-rank approximation helped with quick gesture language identification. *Automatic Face and Gesture Recognition 2015: 11th IEEE International Conference and Workshops, often known as FG 2015*.
- [3] *Using an Eigen Value Weighted Euclidean Distance Based Classification Technique*, Singha J. and Das K. recognize Indian gesture language. 2013; 4(2): p. 188–195. *arXiv preprint arXiv:1303.0634*.
- [4] *System for Recognizing Gesture Language*, Kalsh EA, Garewal NS. 2013; 03(6): p. 15–21 in *International Journal of Computational Engineering Research*.
- [5] Tewari, D. and Srivastava, S. *Visual Recognition of Static Hand Gestures in Indian Gesture Language based on Kohonen Self-Organizing Map Algorithm*. 2012; 2(2): pp. 165–170 in the *International Journal of Engineering and Advanced Technology (IJEAT)*.
- [6] *Indian Gesture Language Recognition Using SVM 1*. Raheja JL, Mishra A, Chaudhary A. *Pattern Recognition and Image Analysis*. 2016 September; 26. (2).
- [7] *4-Camera model for gesture language recognition using elliptical Fourier descriptors and ANN*, Kishore PVV, Prasad MVD, Prasad CR, Rahul R.
- [8] *In Proceedings of the 2015 International Conference on Gestural Processing and Communication Engineering Systems, in Association with the IEEE; 2015*. p. 34–38.
- [9] Sharma, Shanu, Ishita, and Goyal, Sakshi. *System for Recognizing Gesture Language in Deaf and Dumb People*. 2013 April; 2 *International Journal of Engineering Research & Technology (IJERT)* (4).
- [10] Li H, Li W, Huang J, Zhou W. using 3D convolutional neural networks to recognize gesture language. 2015: *IEEE*. p. 1-6. In *Multimedia and Expo (ICME), 2015 IEEE International Conference on*.
- [11] Chen X, Chai X, Li G, Lin Y, Xu Z, and Tang. *Kinect's recognition and translation of gesture language IEEE's 10th International Conference on Automatic Face and Gesture Recognition 2013*; p. 22-26.