GESTURE BASED COMMUNICATION USING PYTHON

MINOR PROJECT-1 REPORT

Submitted by

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BONAFIDE CERTIFICATE

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO HAND GESTURE RECOGNITION

In today's interconnected world, effective communication is paramount. Technological advancements have transcended geographical barriers, turning the globe into a seamless village. Whether for information sharing, business transactions, or maintaining social connections, communication is the linchpin of our modern society. Businesses rely on it for negotiations and collaborations, while social media facilitates personal relationships and cultural exchange. Education, too, has evolved with online platforms emphasizing the importance of communication in knowledge dissemination. In the realm of politics and social movements, communication serves as a catalyst for advocacy and change. During emergencies, it becomes a crucial tool for coordination and information dissemination. In essence, communication is the backbone of our interconnected reality, playing a pivotal role in both the practical aspects of daily life and the rich tapestry of human relationships, ideas, and cultures.

Non-verbal individuals grapple with significant challenges stemming from the absence of conventional communication channels. A primary hurdle lies in the articulation of thoughts, feelings, and needs. Verbal communication, a widely accepted medium for expressing internal experiences, is not available to non-verbal individuals, leading to frustration, potential misunderstandings, and a heightened sense of isolation. The intricacies of social interactions compound these difficulties, as non-verbal cues such as facial expressions, gestures, and body language, which play a pivotal role in conveying emotions and intentions, are not readily accessible. This limitation can result in misinterpretations of social situations, hindering the formation of connections and full participation in social activities. Additionally, the lack of verbal communication may contribute to the misconception that non-verbal individuals are disinterested or unengaged, further impeding their social integration.

Educational environments pose another set of challenges. Traditional teaching methods heavily rely on verbal communication for instruction and understanding. Non-verbal individuals may find it challenging to express comprehension, seek clarification, or actively engage in classroom discussions,



Figure 1.1: Sample of hand sign gestures

potentially affecting their academic progress. In response, there is a growing recognition of the need for inclusive and accessible educational strategies that accommodate diverse communication styles and ensure equitable learning opportunities for non-verbal individuals. Healthcare encounters present yet another layer of complexity. Communicating symptoms, pain levels, or specific health concerns without the use of verbal language may lead to misunderstandings, delays in diagnosis, or inadequate treatment. Effective communication strategies between healthcare providers and non-verbal individuals are essential to ensure accurate assessment, proper medical care, and a positive healthcare experience. Some commonly used hand sign gestures are given in Figure 1.1

The absence of verbal communication channels poses multifaceted challenges for non-verbal individuals across personal, social, educational, and healthcare contexts. Addressing these challenges requires a comprehensive approach that includes alternative communication methods, increased awareness, and the establishment of inclusive environments that recognize and support the unique communication needs of non-verbal individuals.

1.1.1 Overview of Gesture-Based Communication

Gesture-based communication is a form of non-verbal communication that relies on hand gestures, facial expressions, body movements, and other physical cues to convey messages and interact with devices or systems. Unlike traditional methods of communication such as speech or text, gesture-based communication offers a more natural and intuitive way for humans to interact with technology.

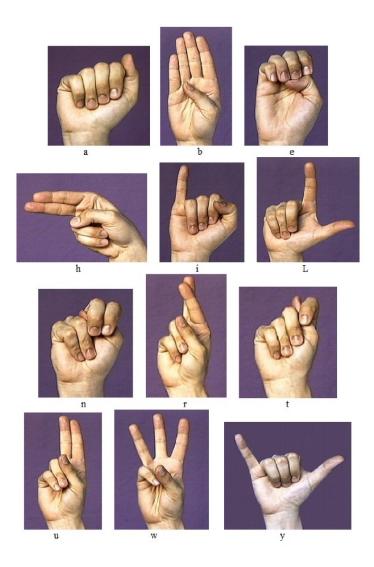


Figure 1.2: Commonly used hand signs

In gesture-based communication, individuals use their hands and body to express emotions, convey information, or control devices. Hand gestures, in particular, play a crucial role in this mode of communication as they can represent specific actions, commands, or symbols. For example, a simple thumbs-up gesture may convey approval or agreement, while a waving motion may signal a greeting or farewell. Some commonly used hand signs are dipicted in figure 1.2. Gesture-based communication systems leverage technologies such as computer vision, machine learning, and sensor technology to detect and interpret hand gestures in real-time. These systems typically consist of input devices such as cameras or depth sensors, gesture recognition algorithms, and communication interfaces. By analyzing the spatial and temporal characteristics of hand movements, these algorithms can identify and interpret different gestures, allowing users to interact with devices or applications without the need for physical input devices such as keyboards or touchscreens.

To address the challenge of limited familiarity with hand sign language among the general population, we are actively developing a sophisticated software solution. This innovative technology

is designed to recognize hand sign language gestures and seamlessly translate them into both text and voice outputs. By harnessing advanced algorithms and machine learning capabilities, our software aims to bridge communication gaps for non-verbal individuals, allowing them to express their needs and engage in effective communication with the wider community. This groundbreaking solution seeks to enhance accessibility and inclusivity by providing real-time interpretation of hand sign language, facilitating a more connected and understanding society. As we strive to refine and optimize this software, our commitment remains focused on creating a tool that empowers individuals who rely on non-verbal communication, fostering a more inclusive environment where everyone can participate actively and communicate with ease.

1.2 SIGNIFICANCE OF PYTHON IN GESTURE BASED COMMUNICATION

Python, as a versatile programming language, plays a significant role in the development of gesture-based communication systems due to several key advantages it offers:

- Simplicity and Readability: Python is renowned for its clean and readable syntax, making
 it accessible to developers of all skill levels. This simplicity accelerates the development process
 and facilitates collaboration among team members working on gesture-based communication
 projects.
- 2. Extensive Libraries and Ecosystem: Python boasts a rich ecosystem of libraries and frameworks tailored for machine learning, computer vision, and signal processing essential components in gesture recognition systems. Libraries such as OpenCV, scikit-learn, TensorFlow, and PyTorch provide powerful tools and algorithms for image processing, feature extraction, and machine learning, enabling developers to implement complex gesture recognition algorithms with ease.
- 3. Flexibility and Expressiveness: Python's flexibility allows developers to experiment with different approaches and algorithms for gesture recognition and interpretation. Its dynamic typing and high-level abstractions enable rapid prototyping and iteration, allowing developers to quickly test and refine their ideas.
- 4. Community Support and Documentation: Python benefits from a vibrant and supportive community of developers, researchers, and enthusiasts who actively contribute to its ecosystem. The abundance of online resources, tutorials, and documentation makes it easier for developers to learn and master Python for gesture-based communication projects. Additionally, the availability of pre-trained models and code samples further accelerates development and reduces the time-to-market for gesture recognition systems. Figure 1.3 shows the process of data collection.

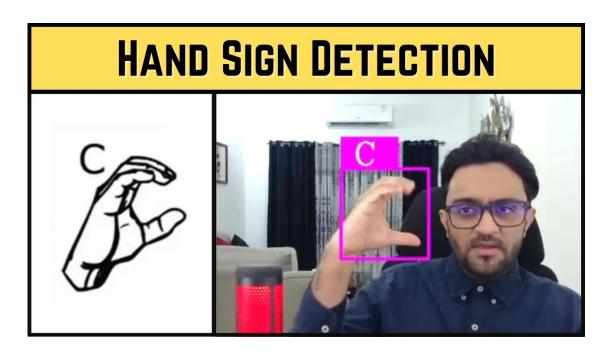


Figure 1.3: Data collection

- 5. Integration with Hardware and Platforms: Python's versatility extends beyond software development it also facilitates integration with hardware devices and platforms commonly used in gesture-based communication systems. Python libraries such as PySerial enable communication with micro controllers and embedded systems, allowing developers to interface with sensors, actuators, and other peripherals used in gesture recognition hardware.
- 6. Scalability and Performance: While Python is often criticized for its performance compared to lower-level languages like C or C++, advances in Python's runtime performance (e.g., with the introduction of Just-In-Time compilation in recent versions) have mitigated many performance concerns. Moreover, Python's scalability and support for parallel processing and distributed computing enable developers to build gesture-based communication systems capable of handling large datasets and real-time processing requirements.

CHAPTER 2

LITERATURE SURVEY

2.1 OVERVIEW

Gesture-based communication systems leverage human gestures to facilitate intuitive interaction with digital devices and environments across diverse applications. These systems enable natural and immersive human-computer interaction, revolutionizing domains such as virtual reality, gaming, healthcare, education, and accessibility. By interpreting hand gestures, these systems empower users to control devices, communicate in sign language, enhance gaming experiences, and access digital resources with ease. From enabling hands-free operation in automotive interfaces to providing assistive technologies for individuals with disabilities, gesture-based communication systems continue to shape the future of human-machine interaction, offering seamless and intuitive ways to engage with technology.

2.2 EXISTING RESEARCH ON GESTURE BASED COMMUNICATION

Research in gesture-based communication has evolved to address nuanced challenges, such as discriminating between standard and nonstandard sign language actions in educational contexts. Traditional sign language recognition models typically focus on recognizing predefined categories, which may not adequately cater to the needs of learners in sign language education software. To bridge this gap, recent studies have proposed novel models that integrate hand detection and standard sign language discrimination methods. According to [1] The paper which introduced a sign language category and standardization correctness discrimination model specifically tailored for sign language education. This model utilizes innovative techniques, including flow-guided features for hand detection and an encoder-decoder structure for sign language correctness discrimination. Author of [5] has explained about the encoder model incorporates 3D convolution, 2D deform able convolution, and residual structures, supplemented by a sequence attention mechanism. Furthermore, researchers have developed dedicated datasets, such as the Sign Language Correctness Discrimination dataset (SLCD dataset), to facilitate the training and evaluation of these models. The SLCD dataset includes videos with dual recognition labels, sign language category, and standardization category, enabling comprehensive

assessments of model performance. The author [2] has proposed the semi supervised model using RCNN and FPN algorithm as shown in Fig: 2.1. Notably, the research community has leveraged semi-supervised learning methods to augment datasets and improve model robustness. These advancements underscore the ongoing efforts to enhance continuous sign language recognition through innovative techniques, such as encoder-decoder architectures and video object detection, paving the way for more inclusive and effective sign language education software.

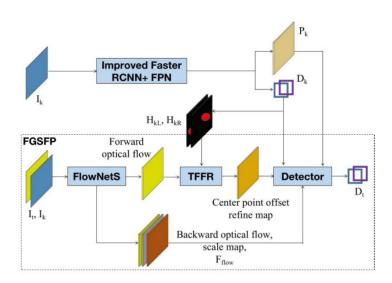


Figure 2.1: Structure of the proposed video hand detection model. The improved Faster RCNN+FPN is used in key frames, and FGSFP+TFFR is used in non-key frames.

In [2] author has proposed the field of gesture-based communication has witnessed significant advancements, as evidenced by a multitude of research endeavors aimed at enhancing human-computer interaction (HCI) through intuitive hand gestures. Various studies have explored dynamic hand gesture recognition systems, emphasizing real-time processing and accurate gesture interpretation. For instance, [3] proposed a real-time dynamic hand gesture recognition system that effectively recognized eleven hand gestures representing numbers one through nine. The author in [6] has approached utilized the YCbCr color space transformation to detect skin color and isolate hand contours from complex backgrounds. Convex defect character points were defined to calculate finger angles and fingertip positions, enabling accurate gesture recognition with an impressive recognition rate of 95.1 percent. Moreover, the study highlighted the importance of computer vision technologies, such as OpenCV, in facilitating gesture recognition tasks.

Prior research has underscored the significance of gesture recognition in HCI applications, emphasizing the need for dynamic and real-time identification of hand gestures. Traditional methods often relied on template matching or hand shape feature matching, which, while robust, may not suffice for HCI applications demanding full hand gesture recognition. Consequently, recent studies

have focused on dynamic gesture recognition systems capable of interpreting gestures in real-time, thereby enhancing user experience and interaction efficiency. The utilization of various image capture devices, including web cameras and depth sensors like Microsoft Kinect, has enabled researchers to capture dynamic hand gestures effectively.

Existing literature [2],[3],[6] and all has explored different techniques for hand detection and feature extraction. Common approaches include skin color detection to isolate hand regions and contour analysis to extract hand features. For instance, methods such as morphological processing and convex hull algorithms have been employed to refine hand contours and identify key features for gesture recognition. Furthermore, studies have investigated the calculation of finger angles and fingertip positions as crucial parameters for distinguishing between different hand gestures. Overall, existing research on gesture-based communication demonstrates a concerted effort towards developing real-time and accurate gesture recognition systems. By leveraging advancements in computer vision, machine learning, and sensor technologies, researchers aim to create intuitive interfaces that enable seamless interaction between humans and machines, paving the way for innovative HCI applications in various domains, including smart homes, gaming, and robotics.

2.2.1 Technologies and Approaches in Gesture Recognition

Gesture recognition encompasses a diverse array of technologies and approaches aimed at interpreting human gestures for various applications, including human-computer interaction, sign language recognition, and virtual reality gaming. Researchers have explored numerous techniques to enable accurate and real-time recognition of gestures, leveraging advancements in computer vision, machine learning, and sensor technologies.

1. Computer Vision Techniques: Computer vision plays a pivotal role in gesture recognition systems by enabling the detection and tracking of hand movements. Traditional methods often rely on image processing algorithms to extract relevant features from input images or video streams. These features may include hand contours, color distributions, and motion trajectories. Techniques such as skin color detection, contour analysis, and optical flow estimation are commonly used to identify and track hand gestures in real-time.

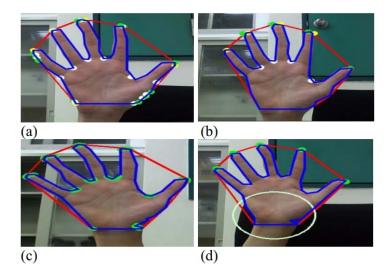


Figure 2.2: (a) All convex defect points of one hand contour with three character points: starting point (green point), end point (yellow point), depth point (white point) and contour convex hull (red line). (b) Remove depth points which have small depth. (c) Feature candidate points of fingertips. (d) Removed candidate points in the interior of the circle and the points with obtuse angles

2. Machine Learning Algorithms: Machine learning algorithms, particularly deep learning models, have revolutionized gesture recognition by enabling more robust and accurate recognition systems. Convolutional Neural Networks and Recurrent Neural Networks are commonly employed to learn complex patterns and temporal dependencies from gesture data. Researchers utilize large-scale datasets to train these models, allowing them to generalize well to diverse gestures and environments. Transfer learning techniques, facilitate the adaptation of pre-trained models to specific gesture recognition tasks, reducing the need for extensive labeled data.

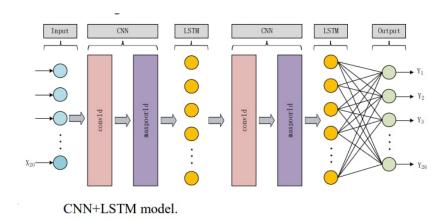


Figure 2.3: CNN with LSTM model

3. Sensor Technologies: In addition to computer vision techniques, sensor technologies play a crucial role in capturing gesture data accurately. Depth sensors, such as Microsoft Kinect and LiDAR devices, provide depth information that complements visual data, enabling more robust gesture recognition in varying lighting conditions and backgrounds. Wearable sensors, such as inertial measurement units (IMUs) and electromyography (EMG) sensors, offer an alternative approach to gesture recognition by capturing motion and muscle activity directly from the user's body.

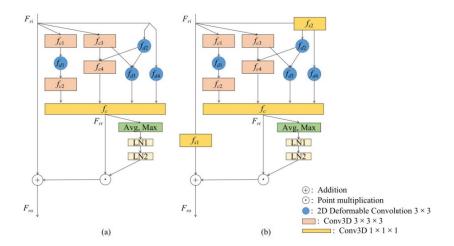


Figure 2.4: Structure of DCSR3D residual block structure, which combines 3D convolution, and 2D deformable convolution. The final result is obtained by the four-path convolution result, and a sequence attention mechanism is implemented. (a) general convolution residual block of DCSR3D; (b) convolution residual block of DCSR3D in down-sampling.

- 4. Fusion of Modalities: Researchers often explore the fusion of multiple modalities, such as visual and inertial data, to improve the robustness and accuracy of gesture recognition systems. Fusion techniques combine information from different sensors or data sources to compensate for their individual limitations and exploit complementary information. For example, combining depth data from a depth sensor with RGB images enhances hand detection and tracking accuracy in challenging environments.
- 5. Real-Time Processing: Achieving real-time performance is a critical requirement for many gesture recognition applications, particularly those involving interactive systems or immersive experiences. Researchers employ optimization techniques, parallel processing, and hardware acceleration to accelerate inference and reduce latency in gesture recognition pipelines. Efficient algorithms and lightweight network architectures enable gesture recognition systems to operate in real-time on resource-constrained devices such as smartphones and embedded platforms.

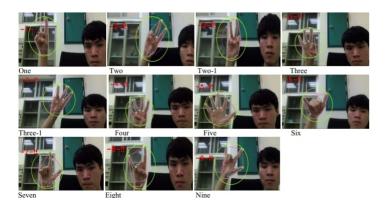


Figure 2.5: The 11 gestures results which present from number one to nine. (finger-tip(green point)), contour convex defects of the start and the end points(white point), contour convex defects of depth(light blue point).

Overall, technologies and approaches in gesture recognition continue to advance rapidly, driven by ongoing research efforts and the growing demand for intuitive and immersive human-computer interaction experiences. By combining insights from computer vision, machine learning, and sensor technologies, researchers strive to develop robust, accurate, and real-time gesture recognition systems capable of supporting diverse applications across domains such as education, healthcare, and entertainment.

2.2.2 Applications of Gesture-Based Communication Systems

Gesture-based communication systems have a wide range of applications across various domains, revolutionizing human-computer interaction and enabling intuitive communication methods. These systems leverage the interpretation of human gestures to facilitate interaction with digital devices, immersive experiences, and assistive technologies. Here are some key applications of gesture-based communication systems:

- 1. Human-Computer Interaction (HCI): Gesture-based communication systems enhance HCI by providing natural and intuitive interaction methods. Users can control computers, smartphones, and other digital devices through hand gestures, eliminating the need for traditional input devices like keyboards and mice. This application finds use in diverse settings, including home automation, gaming, virtual reality, and augmented reality.
- 2. Virtual Reality (VR) and Augmented Reality (AR): Gesture recognition technology is integral to creating immersive VR and AR experiences. Users can interact with virtual environments and manipulate digital objects using hand gestures, enhancing the sense of presence and immersion. Gesture-based interactions enable natural movements and interactions within virtual and augmented spaces, facilitating applications such as training simulations, architectural visualization, and virtual prototyping.

- 3. **Gaming:** Gesture-based communication systems revolutionize the gaming industry by providing more immersive and interactive gameplay experiences. Players can control characters, perform actions, and navigate virtual worlds using hand gestures, enhancing gameplay realism and engagement. Gesture recognition technology enables innovative gaming experiences, such as motion-controlled games, fitness games, and gesture-based puzzles.
- 4. Sign Language Recognition: Gesture-based communication systems play a crucial role in recognizing and interpreting sign language gestures, facilitating communication for individuals with hearing impairments. These systems can translate sign language gestures into text or speech, enabling deaf or hard-of-hearing individuals to communicate effectively with others. Sign language recognition applications find use in education, communication devices, and accessibility tools.
- 5. **Healthcare and Rehabilitation:** Gesture-based communication systems have applications in healthcare and rehabilitation settings, where they are used for gesture-controlled medical devices, rehabilitation exercises, and patient monitoring systems. Patients with mobility impairments or limited motor control can use gesture-based interfaces to interact with medical equipment, access healthcare information, and participate in therapeutic activities.
- 6. Education and Training: Gesture-based communication systems enhance educational experiences by providing interactive learning environments and immersive training simulations. Teachers and trainers can use gesture recognition technology to create engaging educational content, interactive presentations, and virtual laboratories. Gesture-based interfaces enable hands-on learning experiences, facilitating understanding and retention of complex concepts.
- 7. Assistive Technology: Gesture-based communication systems serve as assistive technologies for individuals with disabilities, empowering them to access digital resources, communicate effectively, and perform daily tasks independently. These systems can be customized to accommodate diverse needs, including gesture-controlled wheelchairs, environmental control systems, and communication aids for non-verbal individuals.
- 8. Automotive Interfaces: Gesture-based communication systems are increasingly integrated into automotive interfaces, allowing drivers to control infotainment systems, navigation, and vehicle settings using hand gestures. Gesture recognition technology enhances driver safety and convenience by minimizing distractions and enabling hands-free interaction with in-car systems.

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