Deep Learning-Based Real-Time Hand Landmark Recognition with MediaPipe for R12 Robot Control

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***Abstract*—In the evolving world of robotics, the way humans and robots interact plays a crucial role in the overall system performance and user experience. Traditionally, robotic control for accomplishing tasks have been dominated by programming languages like ROBOFORTH or touchpad interfaces. However, these methods often create barriers to user interaction. This study explores the potential of hand gesture recognition, specifically focusing on the deep-learning MediaPipe library's real-time hand-landmark detection capabilities. We present a system that combines MediaPipes abilities with controlling the ST Robotics R12 robot, allowing real-time hand gestures to be translated into robotic drawing actions and tasks. This integration offers a natural and interactive communication medium that could revolutionize how humans carry out tasks with robots. By leveraging MediaPipes computer vision and deep learning techniques, we successfully controlled the R12 robot through gesture-based interactions. The system effectively translated hand gestures into robotic drawing functions and specific tasks such as object relocation. However, future improvements should concentrate on enhancing precision, reevaluating reliance on ROBOFORTH and exploring MATLAB Simulink's potential for advanced gesture-based control algorithms.**

***Index Terms*—Deep learning, Machine learning, Computer vision, Robotic, MediaPipe, ROBOFORTH**

I. Introduction

In the changing field of robotics, how humans interact with robots plays a crucial role in determining the overall effectiveness and user satisfaction [1]. Previously, controlling robots for tasks like drawing required a deep understanding of specialized programming languages like ROBOFORTH [2]. Alternatively, touchpad interfaces provided a visual approach but still created a barrier between the user's intention and the robot's response [3]. Both these traditional methods have their challenges: direct coding can be overwhelming and intimidating for non-experts [4], while touchpad interfaces, although more user-friendly, may not fully capture the subtleties and intentions behind a users desired action [5].

The emergence of hand gesture recognition presents a solution to these challenges [6]. As technology advances to enhance intuitive interactions, the ability to express intentions through simple hand movements represents a groundbreaking leap forward [7]. In recent years, there have been significant advancements in the field of recognizing hand gestures. These advancements have been driven by the convergence of computer vision, machine learning and sensor technology. The latest techniques mainly focus on deep learning architectures, convolutional neural networks (CNNs), which have shown exceptional performance in classifying gestures [17]. These models are trained on datasets like the Chalearn dataset, enabling them to accurately understand intricate hand movements [18]. In robotics, integrating recognition systems into control interfaces is becoming increasingly common. Modern robotic systems use algorithms to interpret recognized gestures and perform specific actions, resulting in seamless interactions between humans and robots [19]. Real-time feedback loops further enhance this interaction by allowing robots to adjust their actions based on gesture inputs. Notably, the combination of recognition, with augmented reality (AR) and virtual reality (VR), is pushing boundaries, offering users immersive environments to interact with robotic entities [20].

MediaPipe has emerged as a player in this field with its real-time detection of hand landmarks [8]. Its precision and accessibility make it an excellent choice for bridging the gap between intention and robotic response [10]. In this paper, we introduce a system that utilizes MediaPipe to revolutionize the way humans interact with robots [11]. By enabling users to control a robot's drawing actions through hand gestures, we eliminate the complexity of traditional ROBOFORTH programming and touchpad manipulation [12]. Our approach not only simplifies the interaction process but also promotes inclusivity by allowing individuals who are unfamiliar with robotics to engage effectively [13].

The move towards using hand gestures to control robots has implications for the future going beyond just convenience and accessibility [14]. As robots become more integrated into our lives, it is important to have interfaces that imitate natural human behaviour like hand gestures. These interfaces play a role in making sure that people find it easy to approach and adapt to these machines [15]. Our work aims to contribute to this direction by showcasing the potential of interfaces

in promoting a harmonious coexistence between humans and robots [16].

In the field of robotics technological advancements, our paper introduces a novel integration that has not been previously reported. Even though Mediapipe was used extensively in robotics, to the best of our knowledge, there has been no instance where Mediapipe has been interfaced with the R12 robot. This pioneering approach offers a fresh perspective on the potential interplay between computer vision and robotics, underscoring the significance and innovation of our work in the field.

The structure of this paper is organised as follows: Section II provides a detailed explanation of the the methods used in this work. In Section II-C, we introduce the MediaPipe library and its capabilities in real-time hand landmark detection. Section **??** details the innovative integration of MediaPipe's capabilities with the ST Robotics R12, explaining the translation of real-time hand gestures into robotic drawing functions. We delve into the specific gesture-based interactions and how they correlate to distinct robotic tasks in Section V. In Section III, experimental results, including visual inspections of the robot's performance in drawing and task execution, are presented and discussed. The paper's conclusions are drawn in Section IV with future recommendations and potential enhancements to improve system precision and expand gesture-based control algorithms.

II. Methods and Materials

A. The ST Robotics R12

The ST Robotics R12, depicted in Fig. 1, showcases the blend of human-inspired design and advanced automation technology. With its articulated structure, the R12 mimics the architecture of a human arm and its components are named accordingly [21]. While this design offers versatility, it also presents some challenges like cumulative backlash and compliance across its multiple joints [22]. The R12 has a reach of 500mm from shoulder to wrist with additional span depending on the chosen "end effector ", ensuring precision within its category [23]. It utilizes motors that enable micro-steps of 0.18 degrees each, resulting in an impressive resolution of 0.1mm or finer at the end effector [24]. If integrated, an auxiliary pneumatic gripper operates using air ranging from 3 to 7 bar [25]. The R12 system consists of three components: the robot, the controller, and a computer or terminal. While the primary role of the computer is to program the controller, once programmed, the robot can operate independently without relying on it. However, it is recommended to keep a low-cost terminal during usage for convenience [26].

B. Webcam Setup

To capture real-time video sequences, we utilized the OpenCV library, a widely used open-source computer vision library known for its extensive capabilities in manipulating images and videos [27]. Once we initialized the webcam, the captured video sequences became the input for our hand gesture recognition system, which was implemented using MediaPipe.

Fig. 1. Description of the R12 Robot

C. MediaPipe and Hand Landmark Detection

MediaPipe is a framework that is open source and designed for creating multimodal machine learning pipelines (e.g., video, audio) [28]. When it comes to hand tracking it operates through stages. Initially, a model for palm detection identifies a hand by determining its bounding box within the video frame. Once the palm is detected, MediaPipe switches to its hand landmark model. This model can identify 21 landmarks across the hand Fig. 2 ranging from the wrist to the fingertips [29]. These landmarks play a role as they provide detailed information about hand positions and gestures. The underlying models use a combination of BlazePalm techniques for palm detection and utilize a set of handcrafted rules alongside machine learning to predict the location of hand landmarks in real-time [30].

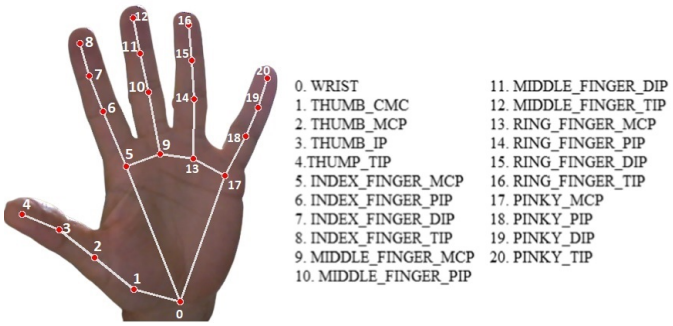

Fig. 2. Handlandmark model ahchitecture

1) BlazePalm Detector: BlazePalm, which serves as MediaPipe's hand position detector, is based on the Single Shot Detector (SSD) approach similar to that of BlazeFace. The main goal of BlazePalm is to locate the palm of a human hand using a convolutional neural network.

One important aspect of BlazePalm's design is its encoder decoder setup for feature extraction. This setup efficiently

captures information from the input and helps in understanding and utilizing these features to precisely detect palms. After detection, the Non-Maximum Suppression (NMS) algorithm [31] comes into play to remove overlapping and redundant bounding boxes, ensuring that only the likely detection for each hand remains.

The overall architecture of their detector can be seen in Fig. 3. It starts with an image size of 256×256. Progressively reduces it; first to 128×128, then halving the dimensions until reaching a final size of 8×8. A noteworthy change they made in their approach is the use of an anchor scheme. This strategic adjustment helped reduce the number of required layers for the model. Their experimental setup incorporated a comprehensive 11,136 anchors, refining the precision and efficiency of palm detection.

To make the model more precise, especially when dealing with imbalanced classes, BlazePalm also includes the use of loss. By giving importance to challenging classifications through minimizing focal loss [32], the model ensures that its performance is not affected by differences between positive and negative examples.

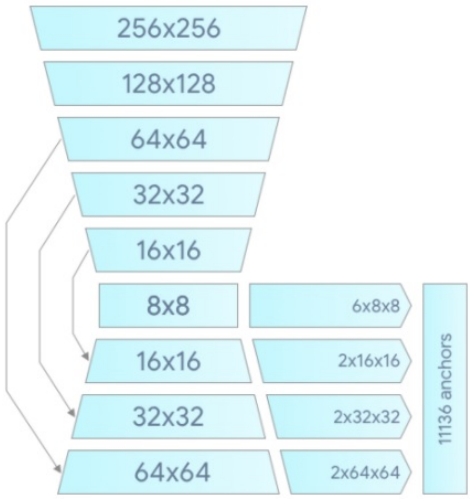

Fig. 3. Mediapipe BlazePalm detector model arhchitecture [9]

2) Hand Landmark Model: The architecture of the Hand Landmark Model is a framework in deep learning that has been designed to identify and locate specific landmarks on the human hand. By utilizing neural networks (CNNs) this framework is trained on extensive datasets containing images of hands to accurately detect crucial points or landmarks such as knuckles and fingertips. These landmarks play a role in various applications, including recognizing gestures, interpreting sign language, creating augmented reality experiences and facilitating human-computer interaction. The model typically consists of layers of convolutions pooling and fully connected layers that work together to process input images and provide the coordinates for each detected landmark on the hand. Advanced techniques for fine-tuning and optimization are employed to ensure that the model can effectively handle diverse hand-shape orientations and lighting conditions, thereby making it adaptable and reliable in real-world scenarios.

In Fig. 4, we can see the structure of the Hand Landmark Model. This model provides three outcomes, each utilizing a feature extractor, as shown. The first outcome identifies the twenty one hand landmarks accurately. Additionally, the second outcome determines whether there is a hand not in the input image by using a hand flag. Lastly, the third outcome indicates whether the identified hand is left or right, referring to [29]. Google's MediaPipe Hands model, as illustrated in Fig. 4 outlines the hand using twenty one landmarks. The starting point is marked as zero. Represents the wrist. Points one to four represent the thumb, points five to eight represent the index finger, points nine to twelve represent the finger, points thirteen to sixteen represent the ring finger and points seventeen to twenty represent the pinky finger.

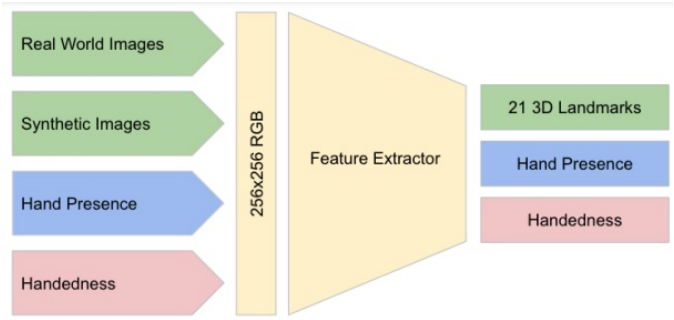

Fig. 4. Mediapipe Hand Landmark detection model [9]

D. Tool Selection Interface

In our user interface there are icons representing drawing tools such as a line, square and circle. Users can easily choose their shapes for drawing by interacting with these icons using hand gestures. We have designed it to be simple and intuitive so that even users who are new to it can quickly understand and navigate through the tool selection process.

E. Translating Hand Movements into Shapes and Tasks

The versatility of our system relies on the MediaPipe's Hand Landmarks model. This model is trained to detect and track 21 landmarks across a detected hand, including points on the palm, wrist and each finger. This level of detail not only helps interpret drawing gestures effectively but also enables the system to recognize specific hand poses for different robotic tasks.

When in drawing mode, the system interprets the dynamics between these landmarks to discern user intent:

- A linear trajectory between two landmarks translates to drawing a straight line.
- A closed-loop traced by the landmarks signals the drawing of a circle.
- Landmark configurations can denote intent to draw shapes like squares, where corners and edges are inferred based on landmark placements.

Beyond drawing, we have also integrated several specific tasks into the system:

1) **Go to Home (Reference Point)**: An open hand gesture directs the robot to move to a predefined 'home' or reference point. This gesture serves as a reset mechanism, ensuring the robot can always return to a known starting position.
2) **Go to Ready Position**: A closed hand signifies the robot should assume a 'ready' stance, preparing it for the next command or drawing task.
3) **Object Movement**: The system is programmed to recognize gestures for moving an object from point A to point B. The specific points are predetermined (hard-coded) within the system, ensuring consistent and reliable object movement upon gesture recognition.

F. Generation of ROBOFORTH Code

Once the system interprets a drawing action, it translates this action into a corresponding set of ROBOFORTH commands. These commands are designed to guide the robot in replicating the drawing.

G. Robot Setup and ROBOFORTH Interpretation

The robot used in our system is equipped with a controller capable of interpreting and executing ROBOFORTH commands. Upon receiving the generated code, the robot's controller deciphers each command, translating it into precise motor movements.

III. Results

In Fig. 5, the sequential steps of the proposed system are highlighted. Initially, the system captures video input from a webcam, which is then processed by OpenCV to segment the video into individual frames. A singular frame is then selected as the main input for the MediaPipe library. Within MediaPipe, the system undergoes a two-phased analysis: palm detection followed by hand landmark detection. Post-detection, the system identifies the orientation of the fingers. Specifically, when the index finger is raised, it grants the operator the capability to navigate the graphical user interface (GUI) and select from one of the four available drawing tools: line, square, circle, or eraser. A sustained hover of the index finger over the desired tool for a duration of two seconds results in its selection. Subsequently, the operator is required to close their hand to initiate the drawing process. Upon completion of the drawing, the system seamlessly translates the design into ROBOTFORTH code. This generated code is then transmitted to the R12 robot through the RS232 serial communication protocol, allowing the robot to execute the given instructions with precision.

However, the specific tasks 'Go To Home', 'Go To Ready Position', and 'Move Object', deviate slightly in their procedure. An open hand gesture (with all five fingers extended) corresponds to the 'Go To Home' command, causing the system to select a predefined ROBOTFORTH code that instructs the R12 robot to its home position. On the other hand, a closed hand gesture designates the 'Go To Ready Position' command, for which there exists a predefined ROBOTFORTH code to move the robot to the ready position. The 'Move Object' task is activated by simultaneously raising both the index and middle fingers. The system interprets this as a command to move an object from a preset point A to point B, already preprogrammed using ROBOFORTH code.

Fig. 6 depicts the results obtained from our conducted experiments. Each row shows a different experiment. There are six rows for the following experiments: draw a line, a square, a circle and execute the 'Go To Home' task, 'Go To Ready' position, and move an object from point A to point B. The primary metric for the validation of our system's capabilities was visual inspection. Given the interactive and visual nature of our approach, this method was deemed most relevant to directly assess the success criteria.

Upon the initiation of a drawing command through hand gestures, the robot proceeded to replicate the intended shape on its drawing surface. The fidelity of the shapes drawn was gauged by visually comparing the robot's output with the user's hand movement representation on the screen. The visual congruence between the user's intent and the robot's output served as a testament to the system's efficacy.

One distinctive aspect of our system is the use of hand movement magnitude to determine the dimensions of the drawn shapes. The size and extent of the shapes were dependent upon the range and motion of the user's hand gestures.

From the results obtained, it is clear that the tasks accomplished and the shapes drawn by the R12 robot are close to the original ones in the case of the drawing tasks and identical in the case of the different tasks (GO TO HOME, GO TO READY and MOVE OBJECT) which proves our method is capable on controlling the robot using computer vision and deep learning. To ensure reproducibility, we have made the videos from our experiments and the accompanying Python source code available on GitHub .

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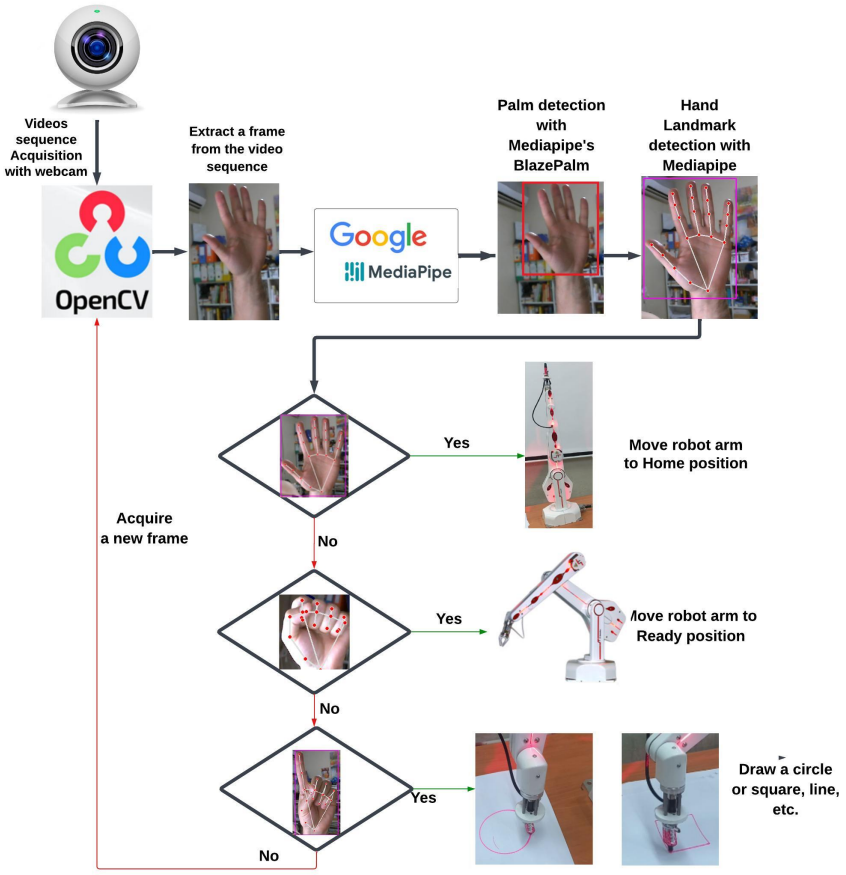

Fig. 5. Flowchart Depicting the Integration of MediaPipe with the R12 Robot

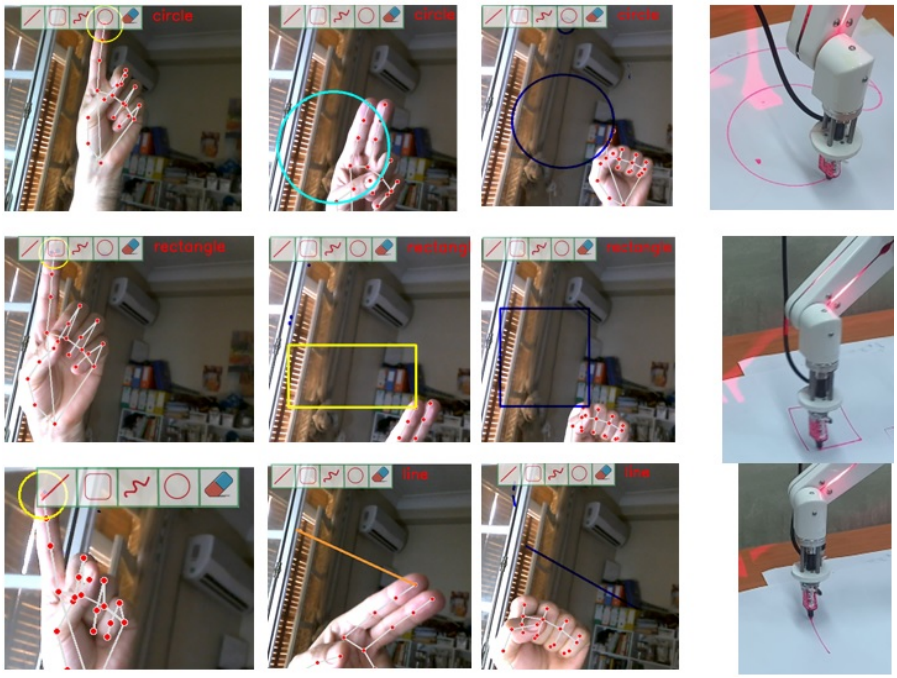

Fig. 6. Sequential Demonstration: From Shape Selection to R12 Robot Execution for a Circle, Square, and Line

IV. Conclusion

In this study, our primary objective was to control the R12 robot, leveraging the power of MediaPipe's computer vision and deep learning capabilities. The outcomes highlighted a system that utilizes the MediaPipe library to convert hand gestures into specific robotic drawing actions. This research highlights the current advancements in gesture-based robotic control. This paper demonstrated that by using hand gestures, our system was able to execute different drawing tasks and other specific tasks like moving an object from point A to point B.

However, there are several enhancements that need to be incorporated into the system. Firstly, refining the precision of the drawn shapes is imperative, as currently, the system lacks the ability to determine exact dimensions. Secondly, reliance on ROBOTFORTH may not be the most optimal choice because it has a limited instruction set, and the user is the one who enters them one by one (using the touchpad). Incorporating MATLAB Simulink, for example, could offer greater accuracy and flexibility. Its Robotics System Toolbox can allow the design of complex control algorithms before deployment that further refine gesture-based control, ensuring greater precision and adaptability.

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