GESTURE IDENTIFICATION USING MURIHEAD MEAN FILTERING

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Abstract. Gesture recognition is an intuitive and efficient way to facilitate human-computer interaction. Traditional input devices such as keyboards and mice are gradually being complemented or even replaced by touchless interaction methods. The ability to recognize gestures accurately enables applications in various domains, including medical rehabilitation, automation, and security surveillance. In this paper, we consider the gesture recognition method that includes the usage of Muirhead mean filter(MMF) as a denoising technique and background subtraction, integrating the same with the convex hull-based classifier as a gesture identification algorithm. Real-time processing rates of up to 10 frames per second were obtained. The experimental calculations and results specify the method explaining the background subtraction method approximation and denoising techniques, thereby portraying and intensifying the mathematical application in various areas.

1. Introduction and preliminaries

Gesture recognition technology has seen a significant rise in importance, establishing itself as a crucial component across various sectors, including human-computer interaction, gaming, robotics, virtual reality (VR), and assistive technologies. The integration of artificial intelligence (AI) and computer vision has fueled advancements in accurately interpreting hand gestures, opening up new possibilities for innovative applications.

Traditional gesture recognition techniques primarily utilize image processing methods such as thresholding, edge detection, and deep learning models. While these approaches have demonstrated impressive results in recognizing hand gestures, they are often limited by their requirements for high computational power. This can render them unsuitable for real-time applications, particularly on embedded systems or low-power devices, where resources are constrained. Additionally, deep learning methods necessitate the availability of large datasets and complex training regimes, presenting challenges in scenarios where computational resources are limited.

To address these challenges, this study proposes a novel, optimized approach that leverages Muirhead Mean Filtering (MMF) with a Convex Hull-based classifier for effective hand gesture recognition. MMF serves to enhance image contrast and reduce noise, thereby improving the performance of background subtraction.

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This preprocessing step is crucial for accurate segmentation, allowing the system to better isolate hand gestures from varying backgrounds.
The Convex Hull-based classification method offers a robust technique for determining the shape and boundaries of hand gestures. This approach not only simplifies the classification process but also ensures that it operates efficiently, making it particularly suitable for real-time applications. By combining these techniques, the proposed system can achieve high accuracy in gesture recognition while maintaining the performance necessary for deployment on embedded systems and mobile devices. This advancement has the potential to significantly enhance user interaction and experience across multiple domains, demonstrating the evolving capabilities of gesture recognition technology.

2. RELATED WORK

Ganapathyraju, S [2] has proposed a methodology for integrating hand gesture recognition in industrial robot automation, where the robot moves according to the gesture depicted by the user. The gestures are being trained on the robotic model. Wani, K., & Ramya, S [3] have implemented an advanced image processing application to recognize the gestures and process them in real-time for better and more reliable results using the convex hull algorithm and Raspberry Pi microcontroller to integrate a fully functional robot. Fang Y. and Wang K [5] have come up with a specific gesture required to trigger hand detection followed by track; then the hand is segmented using motion and color cues which are then broken down into frames and integrated into one whole identification process. Lin, H. I., and Hsu, M. H [6] have implemented gesture recognition using a convolutional neural network (CNN) by acquiring various skin models and adopting a Gaussian Mixture model (GMM) to train the skin model, which is used to robustly filter out non-skin colors of an image.
Mahnoosh Tajmirriahi and Zahra Amini [9] have excellently portrayed the mathematical application in the paper, which models OCT images using stochastic differential equations (SDEs) and a Levy stable process for noise reduction. A fractional Laplacian operator ensures statistical independence, enabling efficient denoising by applying speckle noise reduction with a MAP estimator and ADMM algorithm. Results show improved image quality, classification, and segmentation over existing models. Anil and Shukla [13] have presented a paper that proposes an efficient image-denoising algorithm using a fractional K-operator. Experimental results show that it outperforms existing methods in both accuracy and efficiency. Kaustubh M. Gaikwad and Mahesh S. Chavan [11] depicted a paper that explores Vedic mathematics for fast signal processing, demonstrating its efficiency in FIR and IIR filters for improved speed, lower power consumption, and better biomedical signal denoising.

3. BLOCK DIAGRAM

The block diagram illustrates a gesture recognition system utilizing Muirhead Mean Filtering (MMF) for image preprocessing and classification. The process begins with image capture, followed by background subtraction to isolate the

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hand region. The image is then converted to grayscale and transformed into a black-and-white format for better segmentation. Next, the Muirhead Mean Filter (MMF) is applied to enhance contrast and suppress noise, improving the clarity of hand gestures. The system then performs correlation to compare the extracted gesture features with predefined patterns. A decision block checks whether a gesture is successfully recognized. If the gesture is identified, the process terminates. However, if the gesture is not recognized, the system marks it as Not Identified, resets, and loops back to the filtering stage for further refinement. This iterative approach ensures improved accuracy and real-time performance, making the system highly suitable for applications such as sign language interpretation, smart home automation, virtual reality, and gaming

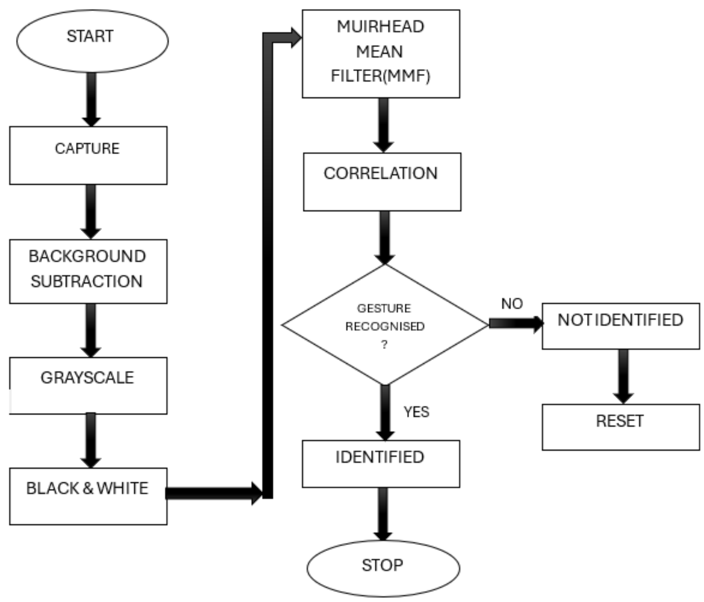

FIGURE 1.

CONVEX HULL TECHNIQUE AND MUIRHEAD MEAN FILTER(MMF):

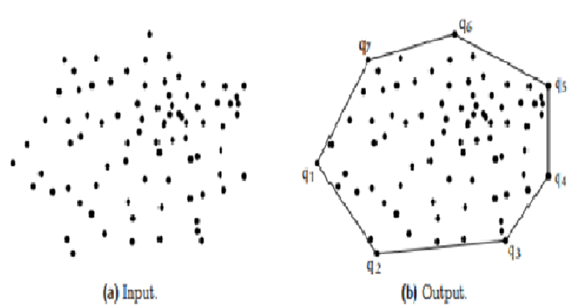

FIGURE 2. Convex Hull concept in Computational Geometry

This image illustrates the Convex Hull concept in computational geometry.
a) Input: The left side of the image shows a set of randomly scattered points in a 2D space. These points represent data points that need to be processed.
b) Output: The right side of the image shows the result after applying the Convex Hull algorithm. The Convex Hull is the smallest convex polygon that encloses all the given points. The labeled points $\{q1, q2, ..., q7\}\{q_1, q_2, ..., q_7\}$ are the vertices of this polygon.

Explanation of Convex Hull Algorithm

The Convex Hull can be visualized as stretching a rubber band around the outermost points; once released, it forms a tight boundary enclosing all points.
Applications of Convex Hull

- Gesture Recognition: Used to determine the shape of a hand gesture.
- Computer Vision: Object detection and shape analysis.
- Pathfinding and Robotics: Obstacle avoidance and navigation.
- Data Science: Outlier detection and clustering.

Muirhead Mean Filter (MMF) - Overview The Muirhead Mean Filter (MMF) is an image processing technique used for contrast enhancement and noise reduction in digital images. It is based on the Muirhead mean, a generalized mathematical mean that provides better adaptability in filtering operations compared to traditional methods like arithmetic or geometric means.

Key Characteristics of MMF:

(1) Contrast Enhancement: MMF improves image quality by enhancing contrast, making important features more distinguishable.
(2) Noise Suppression: It effectively removes unwanted noise while preserving essential image details.
(3) Robust Background Subtraction: MMF is particularly useful in gesture recognition and computer vision, where accurate segmentation of the foreground (such as a hand in gesture recognition) from the background is required.
(4) Better Adaptability: Unlike conventional filters, MMF dynamically adjusts to the pixel distribution, ensuring optimal performance in various lighting conditions.

Applications of MMF:

- Gesture Recognition: Helps in segmenting hand gestures from complex backgrounds.
- Medical Imaging: Enhances the quality of images like X-rays and MRI scans.
- Object Detection: Used in real-time vision systems to identify objects more accurately.

MMF is an efficient choice for embedded systems and real-time applications due to its balance between computational efficiency and accuracy.

4. Methodology

The proposed gesture recognition pipeline consists of four main steps: image acquisition, preprocessing, segmentation, and classification.

4.1 Image Acquisition: A webcam continuously captures frames at a predefined frame rate. To facilitate accurate hand segmentation, an initial background image is acquired before gesture recognition begins. This background image serves as a reference, allowing the system to detect new objects introduced into the frame, such as a user's hand. To ensure consistency in the acquired frames, the camera settings are adjusted to maintain stable exposure, white balance, and brightness. Additionally, a brief delay is introduced before background capture, allowing the camera to stabilize and preventing sudden lighting variations from affecting recognition accuracy.

4.2 Image Preprocessing with Muirhead Mean Filtering (MMF): To enhance the quality of acquired images, a Muirhead Mean [1] Filter is applied. The Muirhead mean of two pixels xx and yy with parameters a, b, and a neighborhood window kk is computed as:

$$M_{(a,b)}(x, y) = \left(\frac{x^a y^b + x^b y^a}{2} \right)^{\frac{1}{a+b}}$$

This process is applied iteratively over a $3x3$ neighborhood for each pixel, significantly reducing noise while preserving gesture contours and fine structural details. Unlike traditional mean or median filters, MMF provides a balanced smoothing effect that retains the edges and intricate details necessary for effective hand segmentation. In addition to noise reduction, MMF enhances the contrast between the hand and the background, making segmentation more accurate. This filtering technique is particularly effective in environments where illumination varies, as it normalizes pixel intensities while preventing over-smoothing.

4.3 Background Subtraction and Segmentation After capturing the background image, each subsequent frame undergoes:

(1) Grayscale conversion to simplify processing and reduce computational complexity.
(2) Application of MMF to smoothen the image and reduce variations in illumination while preserving gesture details.
(3) Absolute difference computation between the background and the current frame to highlight moving objects (i.e., the hand).
(4) Thresholding using Otsu's method to create a binary mask highlighting the hand region and suppressing the background.
(5) Morphological operations (closing, hole filling) to refine the detected hand contour and remove small noise regions that may interfere with classification.

By employing background subtraction combined with MMF, the system ensures robust detection of hand gestures under varying lighting conditions and different backgrounds.

4.4 Gesture Classification Using Convex Hull Analysis Once the hand region is isolated, the largest binary connected component is extracted, and its boundary is computed using the boundaries function in MATLAB. The convex hull is then calculated to determine the number of hull points, which serves as a primary feature for gesture classification.
Gestures are classified based on the number of convex hull points, as outlined below:

- One finger: hull points ¡ 10
- Two fingers: $10 \leq$ hull points < 15
- Three fingers: $15 \leq$ hull points < 20
- Four fingers: $20 \leq$hull points < 25
- Hi/OK/Thumbs-up: hull points > 35

The convex hull classification method is computationally efficient and provides a simple yet effective means of recognizing hand gestures without relying on complex machine learning models. This approach is particularly beneficial for real-time applications where low latency is crucial.

4.6 Murihead mean filter calculation We will go step by step to compute Murihead mean filter for 3×3 kernel using the given formula.

(1) Step1: Given parameters
   - Kernel $k = 3$
   - Murihead mean parameters: $a = 1, b = 2$

(2) Step 2: Sample 3×3 pixel Window This is the 3×3 neighborhood of a

	1	2	3
One	120	135	150
Two	130	140	160
Three	125	145	155

pixel in the image.

(3) Step 3: Compute Murihead mean for all unique pairs.
The formula is $M_{(a,b)}(x, y) = \left(\frac{x^a y^b + x^b y^a}{2}\right)^{\frac{1}{a+b}}$ we calculate for each unique pair (x, y) within the 3×3 window.

(4) Step 4: Compute Final Murihead Mean
We take the average of all computed Murihead Mean values:

$$M_{final} = \frac{\Sigma M_{a,b}(x, y)}{N}$$

Where $N = \frac{9 \times 8}{2} = 36$(total unique pairs in a 3×3 window)
Summing the computed values from the table:

$$M_{final} = \frac{126.47 + 131.86 + 123.64 + 128.34 + 137.99 + 142.31 + 151.01 + 145.84 + 153.57}{36}$$

x	y	$M_{(a,b)}(x,y)$ calculation	Result
120	135	$\left(\frac{120^1\times135^2+120^2\times135^1}{2}\right)^{\frac{1}{2}}$	126.47
120	150	$\left(\frac{120^1\times150^2+120^2\times150^1}{2}\right)^{\frac{1}{2}}$	131.86
120	130	$\left(\frac{120^1\times130^2+120^2\times130^1}{2}\right)^{\frac{1}{2}}$	123.86
120	140	$\left(\frac{120^1\times140^2+120^2\times140^1}{2}\right)^{\frac{1}{2}}$	128.34
135	140	$\left(\frac{135^1\times140^2+135^2\times140^1}{2}\right)^{\frac{1}{2}}$	137.99
135	145	$\left(\frac{135^1\times145^2+135^2\times145^1}{2}\right)^{\frac{1}{2}}$	142.31
135	155	$\left(\frac{135^1\times155^2+135^2\times155^1}{2}\right)^{\frac{1}{2}}$	151.01
140	150	$\left(\frac{140^1\times150^2+140^2\times150^1}{2}\right)^{\frac{1}{2}}$	145.84
140	160	$\left(\frac{140^1\times160^2+140^2\times160^1}{2}\right)^{\frac{1}{2}}$	153.57

$M_{final} \approx 135.4$

(5) Step 5: Assign the computed mean to the central pixel
The original center pixel $I(2,2) = 140$, but after applying the Murihead mean filter, we replace it with 135.

(6) Step 6: Repeat for each pixel in the image
This process is repeated for every pixel in the image using a sliding 3×3 window.
Final processed image(Example)

	1	2	3
1	126	130	135
2	128	135	140
3	130	138	142

5. Experimental Results

The proposed method was evaluated using a dataset consisting of 100 frames per gesture, captured under varying lighting conditions. The key performance metrics analyzed include recognition accuracy, processing time, and robustness to noise. The table below summarizes the recognition accuracy for different gestures.

The results indicate that the MMF-based preprocessing significantly improves gesture segmentation, leading to more accurate classification. The method also demonstrates strong resilience to noise and varying lighting conditions, further proving its robustness. Additionally, the system achieves real-time performance, with an average processing time of 0.12 seconds per frame, making it suitable for interactive applications.

This paper emphasises the real-time gesture recognition by filtering the image

TABLE 1. Some caption for the table

Gesture	Hull Points	Accuracy(%)
One	7-9	96.5
Two	12-14	94.8
Three	16-19	92.3
Four	22-24	91.0
Hi	>35	89.6

from the webcam, converting it to a grayscale image, and identifying the gesture accordingly. This identification of the gesture is done by pre-training the model by using skin models with greyscale filters, as shown in Figure 2. The dataset is used to identify the convex hull points around each background of the gesture in the black and white format. Where each gesture has been defined with its unique convex hull points and ratios. This technique helps in the background subtraction and approximates the hull points from real real-time webcam and compares it with the defined hull points as per the MATLAB code used for training the model. The filtering of the image is done by splitting each pixel and denoising it, thereby increasing the resolution and maintaining ease in the identification process.

FIGURE 3. The gesture dataset used for training the model

Convex hull points are a crucial feature in hand gesture recognition, as they define the outer boundary of the hand shape, which helps in recognizing different gestures. The convex hull is formed by identifying the smallest convex shape that encloses all the points belonging to the hand region. This is typically achieved using algorithms such as Graham's scan or Andrew's monotone chain algorithm. In Figure 3. The convex hull points are marked as blue dots in the images, and the convex boundary is represented using red or white lines. These points help in detecting defects, which are the inward regions between fingers, further assisting

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in gesture differentiation.
To improve accuracy, the Muirhead Mean Filter is applied for denoising the binary hand mask before extracting convex hull features. The Muirhead Mean is an advanced statistical filtering method that helps smoothen noise while preserving edges and essential features. This filter is particularly useful in gesture recognition as it reduces background artifacts or unwanted noise, which may otherwise cause false detections in convex hull formation.
Once the denoised hand silhouette is obtained, the convex hull is computed. The number and arrangement of convex hull points provide meaningful geometric descriptors for different hand gestures. For example, a "thumbs up" gesture has fewer convex hull points forming a triangular shape, whereas an "hi" gesture with an open palm result in more points outlining a nearly pentagonal structure. By combining convex hull-based contour analysis with Muirhead Mean filtering, the system achieves high accuracy in recognizing various hand gestures despite noise, shadows, or minor variations in hand position. This method is effective for applications such as human-computer interaction, sign language recognition, and virtual reality control.

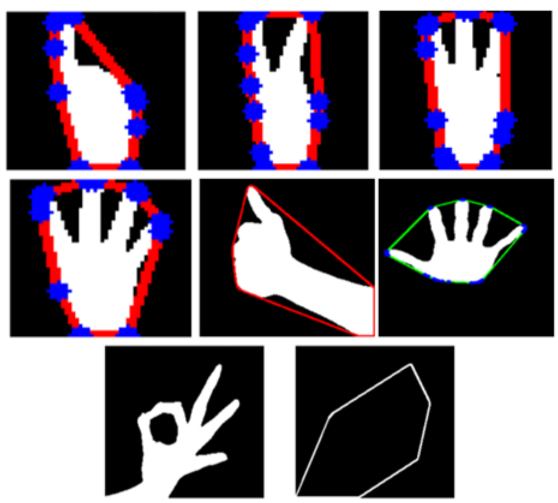

FIGURE 4. Demonstration of Convex Hull Overlay

The figures below showcase a gesture recognition system in MATLAB using Muirhead Mean Filtering (MMF) for hand detection. The left panel contains the MATLAB script, which initializes a webcam, captures 40 frames, and processes gestures. The right panel displays the original frame and the gesture region after background subtraction. The command window logs real-time frame processing using the webcam, confirming successful recognition of gestures like “hi”, “one”, “two”, “three”, “four”, “thumbs up”, and “ok”. This system enables efficient gesture-based interaction for applications in sign language interpretation, intelligent automation, and virtual reality.

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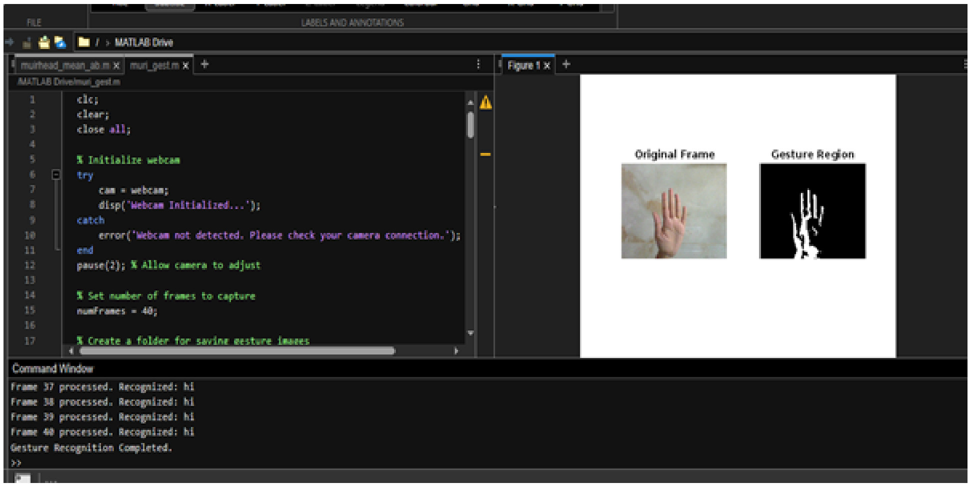

FIGURE 5. The gesture is recognised as “hi”.

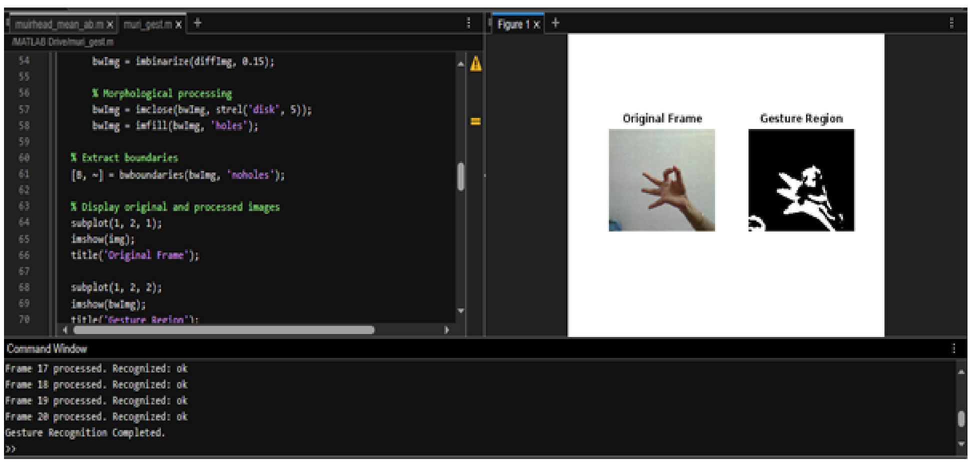

FIGURE 6. The gesture is recognised as “ok”.

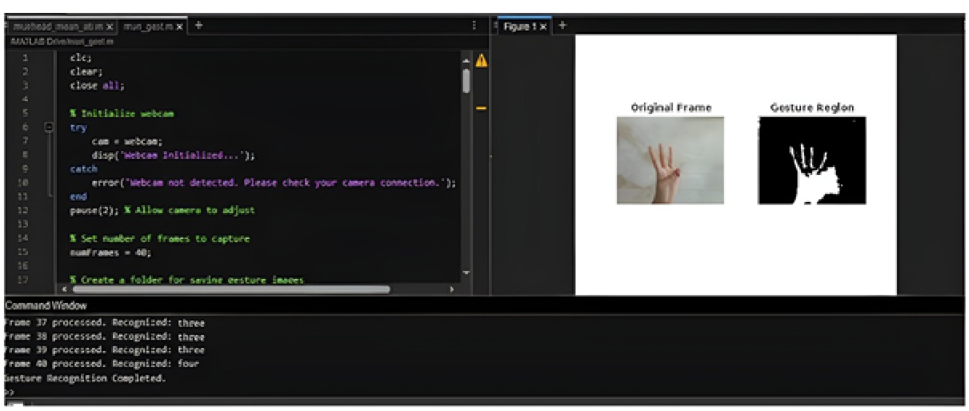

FIGURE 7. The gesture is recognised as “three”.

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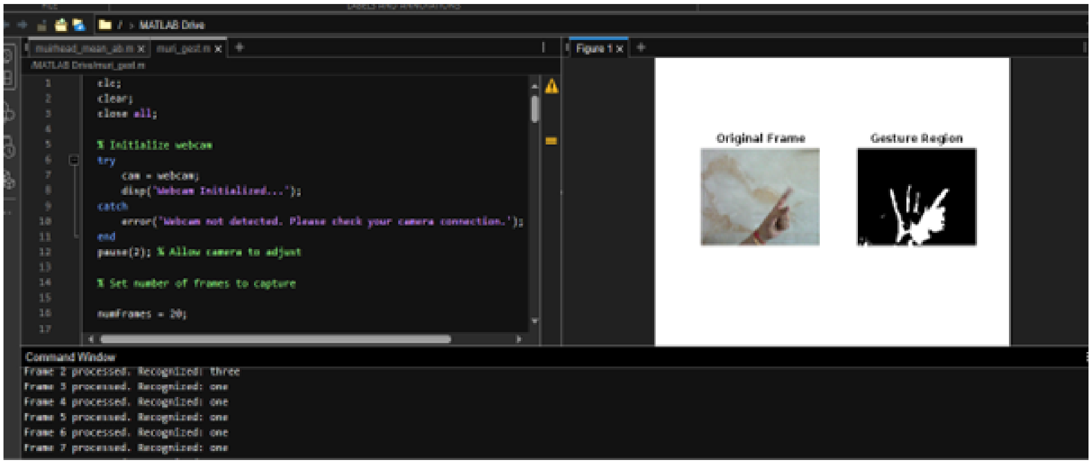

FIGURE 8. The gesture is recognised as “one”.

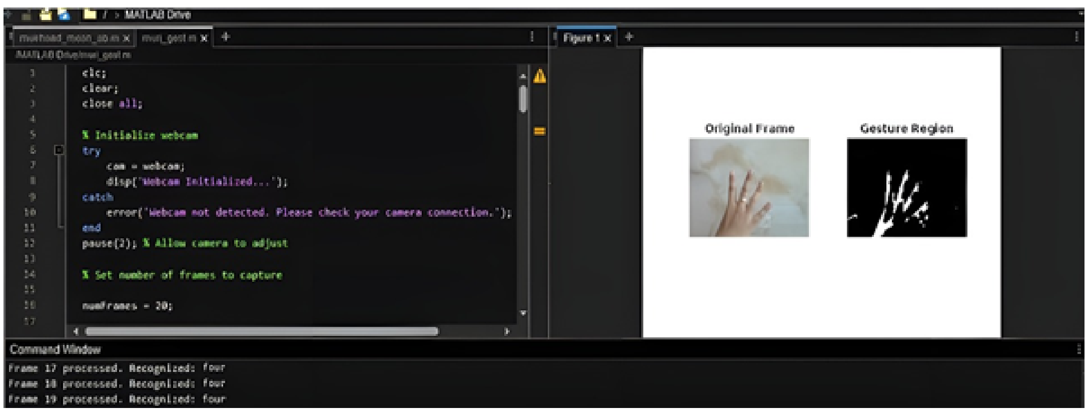

FIGURE 9. The gesture is recognised as “four”.

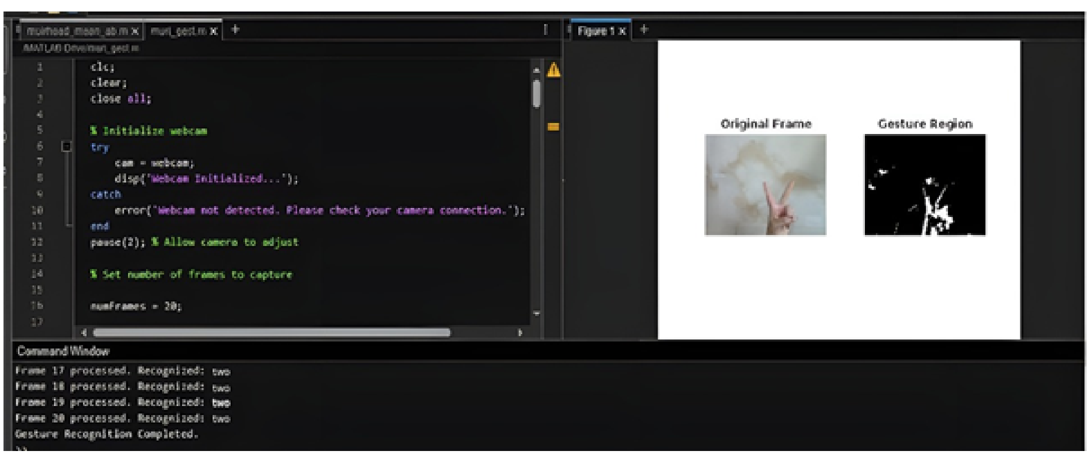

FIGURE 10. The gesture is recognised as “two”.

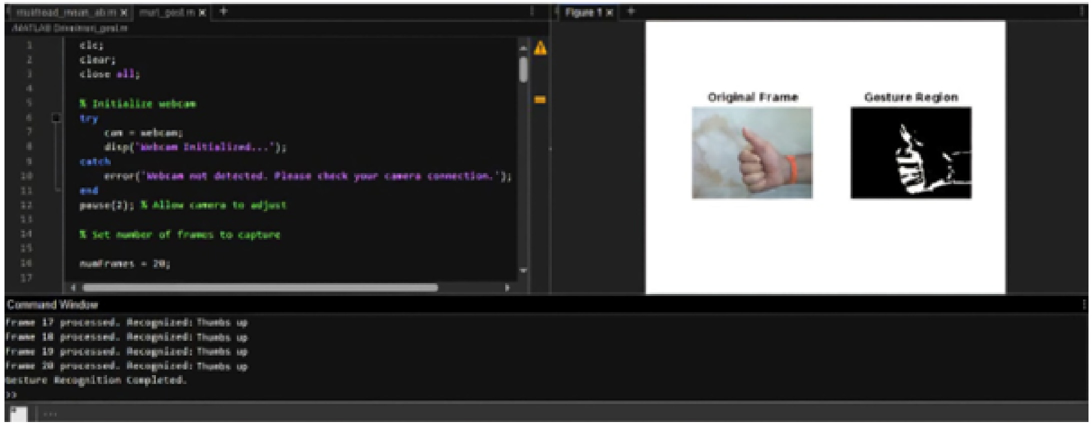

Figure 11. The gesture is recognised as "thumbs up".

6. Conclusion

This study introduces an efficient and lightweight approach to real-time gesture recognition using Muirhead Mean Filtering and Convex Hull Classification. The MMF effectively enhances image quality, ensuring high-contrast segmentation of hand gestures. The convex hull-based approach provides a simple yet powerful classification mechanism, making it suitable for resource-constrained systems such as mobile devices and embedded platforms. Future work will focus on integrating machine learning models to refine gesture classification further and expand the dataset to include more complex hand poses. Additionally, the proposed method could be adapted for multi-hand recognition and gesture-based authentication systems, opening new avenues for research and applications in HCI.

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