Experiment Report:

Image Processing for Stitch Detection

- *Objective*

The primary objective of this experiment was to develop an image processing pipeline to detect and count stitches in a medical incision image. The experiment involved several steps, including converting the image to grayscale, applying thresholding, and detecting contours.

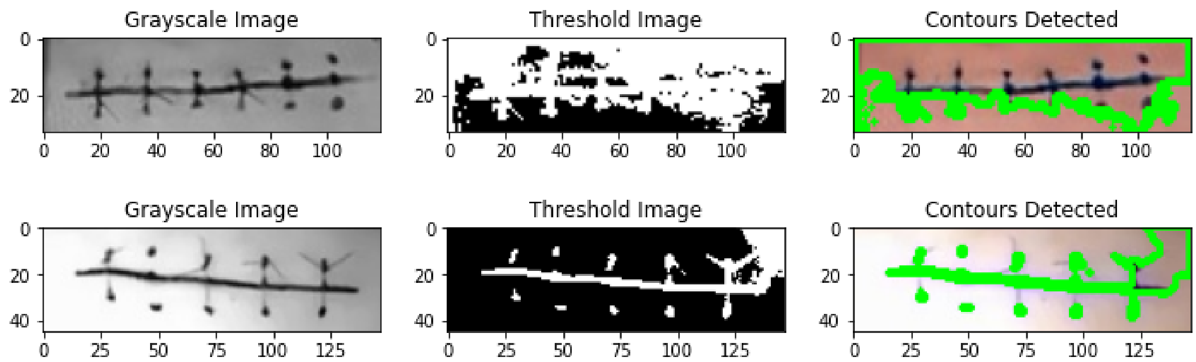
ATTEMPT 1

- *Procedure*

1. Load the Image and convert it to a grayscale image to simplify the subsequent processing steps.
2. Thresholding was applied to the grayscale image to create a binary image, where the pixels corresponding to the stitches would ideally be highlighted.
3. Find Contours in the thresholded image, ideally corresponding to the edges of the stitches. These contours were drawn on the original image for visualization purposes.
4. The grayscale image, thresholded image, and contour-drawn image were displayed using Matplotlib.

- *Results*

The experiment resulted in the following visualizations:



However, the number of stitches detected was not as expected. The method detected a large number of contours that did not correspond to the actual stitches, indicating a high level of noise and false positives.

- *Pros of the attempt 1:*

1. This procedure is relatively simple to implement, as it utilizes basic image processing techniques such as grayscale conversion and thresholding.

2. By using simple methods like thresholding and contour detection, the procedure can be executed quickly, making it suitable for real-time applications.

3. Displaying the original image alongside the thresholded image and detected contours provides a clear understanding of the processing steps and the results obtained.

- *Cons of the attempt 1:*

1. Direct thresholding can be sensitive to noise in the image, which may result in the detection of false or undesired contours that do not correspond to actual points of interest.

2. The outcome of the procedure may significantly depend on the parameters chosen for thresholding and other processing steps, requiring manual adjustments and not guaranteeing optimal detection of points of interest.

3. Since this procedure relies on simple techniques and does not utilize advanced machine learning or image processing methods, it may lack robustness to handle variations in illumination, noise, or appearance of points of interest across different images.

4. This approach may struggle to handle variability in the appearance of points of interest, such as changes in size, shape, or orientation of stitches, leading to inaccurate or inconsistent detection.

ATTEMPT 2

- *Procedure:*

1. The image was loaded and converted to grayscale to simplify subsequent processing steps. Bilateral filtering was applied to the grayscale image to reduce noise while preserving edges.

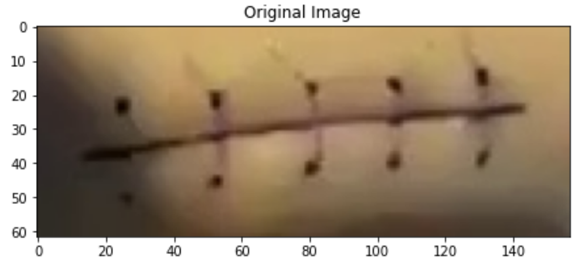
2. Canny edge detection algorithm was employed to detect edges in the preprocessed grayscale image.

3. Contours were extracted from the edge-detected image using the OpenCV function `findContours`.

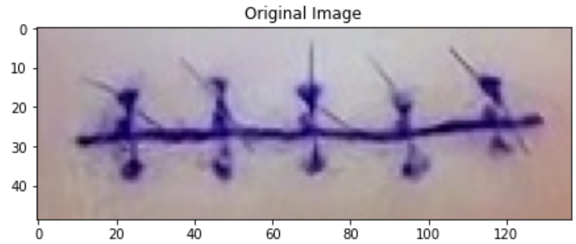
4. The original image and the contours detected were plotted side by side using Matplotlib for visual inspection.

- *Results:*

The experiment resulted in the following visualizations:



Number of stitches detected: 6



Number of stitches detected: 5

- *Analysis:*

Despite a reasonable attempt, the method did not effectively differentiate between stitches and other features in the image. The edge detection technique, along with contour extraction, provided some success in detecting stitch-like features. However, the algorithm detected several false positives, where contours unrelated to stitches were identified. Further refinement of the detection algorithm is required to improve accuracy.

- *Pros:*

1. The procedure utilizes edge detection techniques like Gaussian blur and Canny edge detection, which are effective in highlighting the edges of objects in the image, potentially aiding in identifying stitches.

2. Hough Line Transform: Employing the Hough Line Transform to detect predominantly vertical lines, which ideally correspond to stitches, demonstrates a targeted approach to identifying relevant features, potentially improving accuracy.

3. The visualization of the original image alongside the detected contours provides a clear understanding of the processing steps and the detected features, facilitating interpretation and analysis.

- *Cons*:

1. False Positives The method suffers from false positives, where contours unrelated to stitches are detected. This indicates a lack of specificity in the detection algorithm, leading to inaccurate results.

2. Despite attempting to detect vertical lines corresponding to stitches, the method struggles to effectively differentiate between stitches and other features in the image. This suggests a need for further refinement in the detection algorithm.

3. The performance of the method may heavily depend on the parameters chosen for Gaussian blur, Canny edge detection, and the Hough Line Transform. Inaccurate parameter selection can lead to suboptimal results.

4. The method solely relies on edge detection and line detection techniques, which may not be sufficient to capture all variations and complexities in the appearance of stitches, leading to incomplete detection or missed stitches.

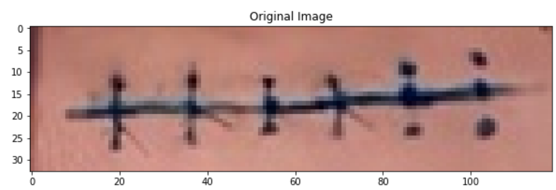
ATTEMPT 3

- *Procedure:*

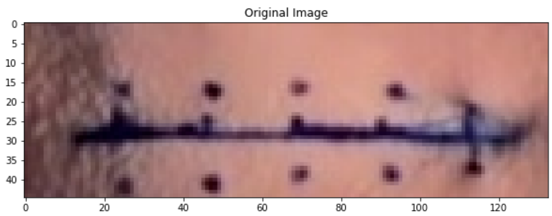
1. The image was loaded and converted to grayscale to simplify subsequent processing steps.
2. Edge Detection: Gaussian blur was applied to the grayscale image to reduce noise, followed by Canny edge detection to detect edges in the image.
3. The Hough Line Transform was employed to detect lines in the edge-detected image. The parameters for the transform were set to detect predominantly vertical lines, which, ideally, correspond to the stitches in the image.
4. Visualization: The original image was plotted using Matplotlib.

- *Results:*

The experiment resulted in the following visualizations:



Number of stitches detected: 9



Number of stitches detected: 5

Despite an improvement on the results, the method did not effectively differentiate between stitches and other features in the image. employing the Hough Line Transform to detect vertical lines corresponding to stitches was a good move, but there was further refinement of the detection algorithm to do. Additionally, false positives were observed, where lines unrelated to stitches were detected.

- *Pros of the attempt 3:*

1. Utilizing edge detection techniques like Gaussian blur followed by Canny edge detection helps in highlighting the edges of objects in the image, potentially aiding in the identification of stitches.

2. The use of the Hough Line Transform for detecting vertical lines, which ideally correspond to stitches, shows an attempt to target specific features relevant to the task, potentially improving accuracy.

3. Displaying the original image alongside the results provides a clear understanding of the processing steps and the detected features, facilitating interpretation and analysis.

- *Cons of attempt 3:*

1. The method suffers from false positives, where lines unrelated to stitches are detected. This indicates a lack of specificity in the detection algorithm, leading to inaccurate results.

2. Despite attempting to detect vertical lines corresponding to stitches, the method struggles to effectively differentiate between stitches and other features in the image. This suggests a need for further refinement in the detection algorithm.

3. The performance of the method may heavily depend on the parameters chosen for Gaussian blur, Canny edge detection, and the Hough Line Transform. Inaccurate parameter selection can lead to suboptimal results.

4. The method solely relies on edge detection and line detection techniques, which may not be sufficient to capture all variations and complexities in the appearance of stitches, leading to incomplete detection or missed stitches.

- *Conclusion:*

Based on the analysis of the procedures presented, Attempt 3 stands out as the most promising approach for stitch detection. Despite its limitations, Attempt 3 employs edge detection techniques, such as Gaussian blur and Canny edge detection, along with the Hough Line Transform, to target specific features relevant to the task. This targeted approach, although not without flaws, demonstrates an attempt to improve detection accuracy by focusing on the detection of vertical lines corresponding to stitches.

While Attempt 3 still faces challenges such as false positives and difficulty in differentiation, its utilization of multiple image processing techniques and a focused strategy makes it the most suitable candidate for further refinement and improvement. With additional fine-tuning of parameters and potential integration of advanced techniques, Attempt 3 has the potential to yield more accurate and reliable results for stitch detection tasks.

Therefore, based on the presented analysis, Attempt 3 emerges as the best attempt among the options provided, offering a solid foundation for future optimization and enhancement of stitch detection algorithms.