COL780 Assignment 1

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1 Introduction

This is a report for the computer vision assignment on Automated Evaluation of Micro-sutures. The code is written in two files, namely main.py and helper.py. main.py imports helper.py and calls the functions from it. Numpy is used for data processing. Pandas is used for reading and writing csv files. OpenCV is used only for reading and writing images. Os and sys are used for reading directories and arguments passed to python code.

2 Counting Number of Sutures

2.1 Preprocessing

For preprocessing, first the image is converted to gray scale image. Then a gaussian kernel of 5 x 5 size is used to smoothen the image. Contrast is increased to make the black sutures appear sharper. Finally thresholding is done to effectively separate the background from sutures. Two sample images are shown before and after preprocessing in Figure 1.

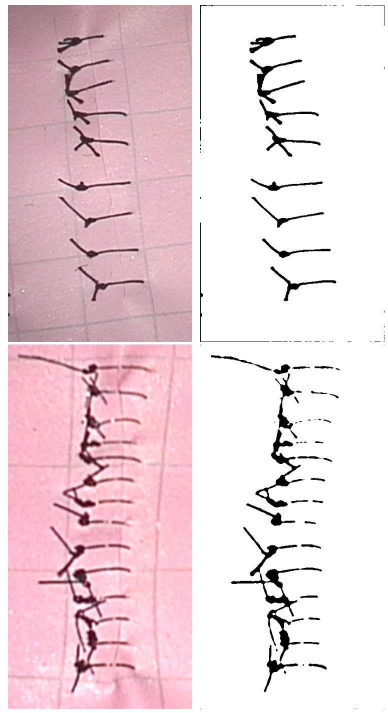

Figure 1: Image before preprocessing (Left), Image after preprocessing (Right)

2.2 Edge Detection

Using Canny edge detector, the edges of image is detected and the image is then converted to a binary image.

Images are cropped after canny edge detection to remove unnecessary pixels. Cropping is done with an offset of 10 px from the closest pixels to each edge of image.

Canny edge detector leads to one pixel thick edges. To make sure that the edges are not lost/ignored in coming steps, the thickness of edge is increased. To decide how much thickness increment can the image tolerate without leading to mixing of different sutures, a dry run of all steps is done without thickening the suture boundary. Then mean inter suture distance is calculated and depending upon its value, thickness is decided which lies from 1 px to 5 px. Increasing thickness depending upon mean inter suture spacing resulted in a high accuracy in suture count. Two sample images are shown before and after canny edge detection, cropping and thickening of edge in Figure 2.

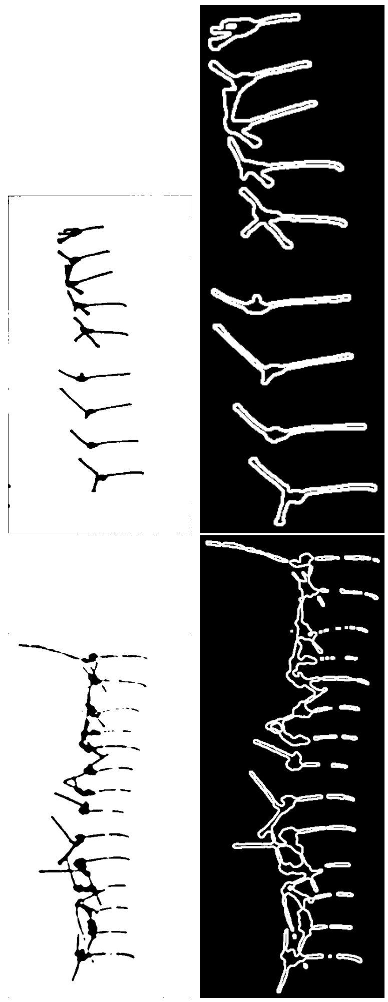

Figure 2: Image before Edge detection (Left), Image after Edge detection (Right)

2.3 Hough Transform

Basic Idea for using the Hough Transform is to filter out the thin line like region of suture (which we may call a stitch), i.e. the parallely inclined part of suture which does not includes its knot. Once we can separate it out then it would be easy to count number of sutures using connected components algorithm.

From the gradient calculated during canny edge detection, approximate angle of the line normal to suture at each point can be calculated. Taking its weighted mean (taking gradient to be weight) over all the points of suture in binary edge detected image can provide an rough approximate of inclination of the line perpendicular to all sutures.

Now we will perform a gradient based hough transform in polar coordinates. The precision for angle and perpendicular distance is taken to be 2 degrees and 1 px respectively. We know the inclination of normal at each point, i.e. approximate inclination of suture at that point. So we will only search for lines with inclination $\pm 6^\circ$ from the approximate known inclination of suture. These parameters are tuned to give best result for the given dataset and current algorithm. Also, we will ignore any point which has its inclination more than 40° from the mean inclination of all images. This is done to make sure that we only consider lines belonging to parallely inclined part of sutures.

Once the lines are detected using hough transform, a new image is created in which all the points belonging to same line are joined (without extending the line any further from both sides). This is done using bresenham algorithm to plot a line between any two points. For each line the leftmost and rightmost points are identified and joined using bresenham algorithm. Two sample images are shown before and after hough transform in Figure 3.

2.4 Splitting Components

Each image after hough transform is splitted in connected components via two pass algorithm. Centroid for each suture is approximated by taking common points from the edge detected image and each connected component and then finding its centroid. It is important to note that only the parallely inclined part of sutures are contributing to this approximated centroid rather than full suture.

It might be possible that single suture is divided into more than one components due to not intersecting group of lines. To tackle this scenario, components whose centroid are less than a certain fraction of mean intersuture distance (along the approximate line perpendicular to all sutures) are combined into single component. This step of finding centroids and combining components is repeated 3 times by taking the fraction to be 1/3, 1/2.5 and 1/2 respectively.

Once the image is classified in different components, each suture being denoted by a component, we can count the total number of components to find the total number of sutures. Two sample images are shown before and after centroid detection in Figure 3. Predicted number of sutures for each of the provided image can be found in Table 1.

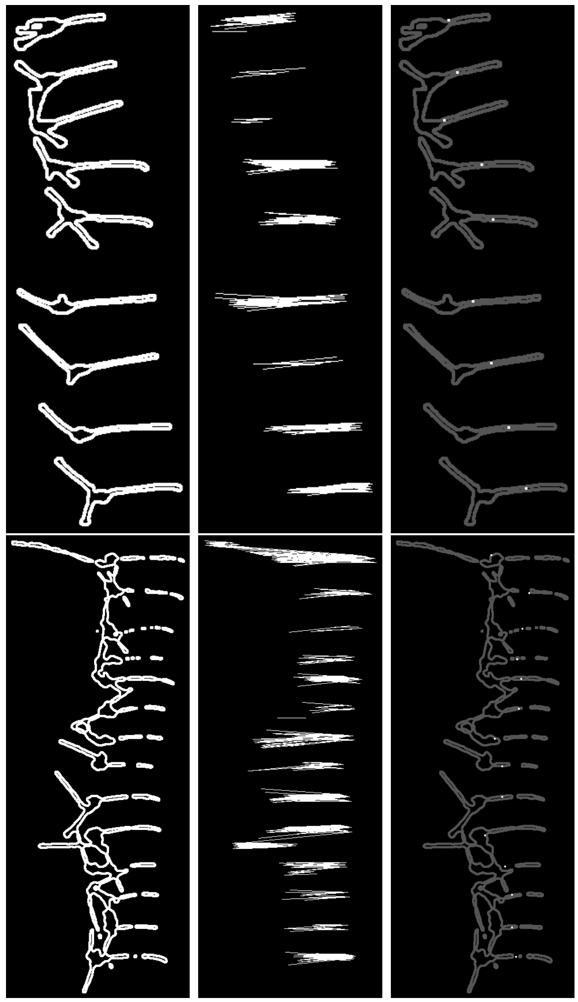

Figure 3: Image before Hough Transform (Left), Image after Hough Transform (Middle), Image after Centroid Detection(Right). In first and second image 9 and 14 centroids are detected respectively, which corresponds to 9 and 14 sutures in the respective images.

3 Inter Stuture Spacing

Once the centroids are calculated, it is easy to find the inter stuture spacing by finding euclidean distance between consecutive centroids. Corresponding statistical quantities can also be determined easily.

All of the above stated facts were justified by finding better suture image based on inter suture spacing feature with different metrics. Predicted mean inter suture spacing and its variance relative to image height for each of the provided image can be found in Table 1.

4 Angulation of the suture

For calculating angulation of suture, common points are taken from the edge detected image (image after canny edge detection) and the components of image found to get the approximate parallely inclined suture as components. Using these common points, taking weighted mean (with gradient as weight) of approximate inclination of line perpendicular to suture at the given point (calculated during canny edge detection), we can get approximate inclination of each line perpendicular to each suture. The inclination of line perpendicular to each of the calculated line can be treated as inclination of each suture. In this way we can find the angulation of each suture. Corresponding statistical quantities can also be determined easily.

Predicted mean value and variance of angle formed by sutures with x axis can be found in Table 1.

Image Name	**Number of Sutures**	**Mean Inter Suture Spacing**	**Variance of Inter Suture Spacing**	**Mean Suture Angle wrt X-axis**	**Variance of Suture Angle wrt X-axis**
img1.png	9	0.0959	0.000243	0.9241	10.4452
img2.png	5	0.0934	0.0010	0.6287	7.6542
img3.png	9	0.1035	0.0003421	0.0376	4.2526
img4.png	10	0.0834	0.0003094	2.8415	12.2467
img5.png	10	0.0892	0.0002865	-1.6137	15.8545
img6.png	12	0.0722	0.0003183	2.0087	16.8272
img7.png	8	0.0974	0.0009338	-0.6555	4.2020
img8.png	15	0.0594	0.0002146	-1.2191	1.0076
img9.png	16	0.0558	0.0001642	-1.1369	4.0308
img10.png	14	0.0692	0.0002581	-4.7286	12.9700

Table 1: Predicted number of sutures, mean and variance of inter suture spacing and angle wrt x axis for each image provided in the data set

5 Comparison of two micro-suturing outcomes

For comparing two micro suturing outcomes, I have used $\frac{\text{std\_dev(Inter Stuture Spacing)}}{\text{mean(Inter Stuture Spacing)}}$ as the parameter for finding best possible arranged suture. Also the inter suture spacing calculated is along the direction of approximate line perpendicular to all sutures. It would be better to measure the perpendicular distance between sutures rather than direct euclidean distance between centroids.

For comparing two micro sutures angulation, variance of angles are directly compared. While calculating angles for each component, the y coordinate of different image is normalized to have same mean inter suture distance, allowing for a better comparison.

The predicted comparison between different images based on these features is tabulated in Table 2.

img1_path	**img2_path**	**output_distance**	**output_angle**
data/img1.png	data/img2.png	1	1
data/img1.png	data/img4.png	1	1
data/img1.png	data/img6.png	1	1
data/img1.png	data/img8.png	1	2
data/img1.png	data/img10.png	1	1
data/img3.png	data/img4.png	1	2
data/img3.png	data/img6.png	1	1
data/img3.png	data/img8.png	1	2
data/img3.png	data/img10.png	2	1
data/img5.png	data/img6.png	1	2
data/img5.png	data/img8.png	1	2
data/img5.png	data/img10.png	2	1
data/img7.png	data/img8.png	2	2
data/img7.png	data/img10.png	2	1
data/img9.png	data/img10.png	2	1
data/img2.png	data/img4.png	2	2
data/img2.png	data/img6.png	2	2
data/img2.png	data/img8.png	2	2
data/img2.png	data/img10.png	2	1
data/img4.png	data/img6.png	1	1
data/img4.png	data/img8.png	1	2
data/img4.png	data/img10.png	2	1
data/img6.png	data/img8.png	2	2
data/img6.png	data/img10.png	2	1

Table 2: Comparison of micro suturing outcomes based on inter suture spacing and suture angulation