# Artificial Vision and Pattern Recognition
# Assignment No. 1

Jason Klimack

Barcelona, Master in Artificial Intelligence

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## Contents

# 1 Introduction

Analyzing thermograms of breasts is a very important method for determining whether or not a patient has breast cancer. However, the location of the nipples plays a key role in order to appropriately analyze the thermograms. Thus, the authors of [1] introduce a novel approach to automatically detect the nipple locations in breast thermograms. In this exercise, I implement the algorithm introduced in the above mentioned article, and apply it to set of test images of breast thermograms.

# 2 Implementation

In this section, I discuss the algorithm that I implemented, the software used, each step taken, and the input/output of the function.

## 2.1 Software and Functions

In this work, I used MatLab to implement the algorithm needed for automatic nipple detection in breast thermograms. There are two MatLab files submitted with this work: *AVPR_A1_Klimack_Jason.m* and *nipple_klimack.m*. The latter file contains the function *nipple_klimack* which takes as input a single grayscale image of a breast thermogram and a boolean value, *display* which is used to toggle whether or not the image should be displayed on the screen upon completion of the algorithm. The return value is a 3x1 cell array, where the first element is the original image, the second element is the x-coordinates of the two nipples, and the third element is the y-coordinates of the two nipples.

## 2.2 Algorithm

The algorithm consists of three main stages: human body segmentation, adaptive thresholding, and nipple detection. Figure 1 shows the output of each step.

**Human body segmentation.** In this step, a body mask, *bmask* was created by thresholding the input image with a predefined value, *btheta=50*. Next, a morphological close operation using a disc-shaped element with radius 3 is applied to the mask, followed by a morphological dilation with disc-shaped element with radius 10. Finally, the mask is applied to the original image in order to segment the human body.

**Adaptive Thresholding.** Adaptive thresholding is used to find candidate nipples in the image. The adaptive thresholding implemented follows three simple steps: 1) apply median filter convolution to the image with a neighbourhood size of 15x15 pixels 2) subtract the segmented image from the convolved image 3) threshold the difference image using a threshold of **0.03**. In other words, if the difference in the pixel intensity between the convolved image and the original is greater than 0.03, then the pixels that satisfy this condition are marked as candidates.

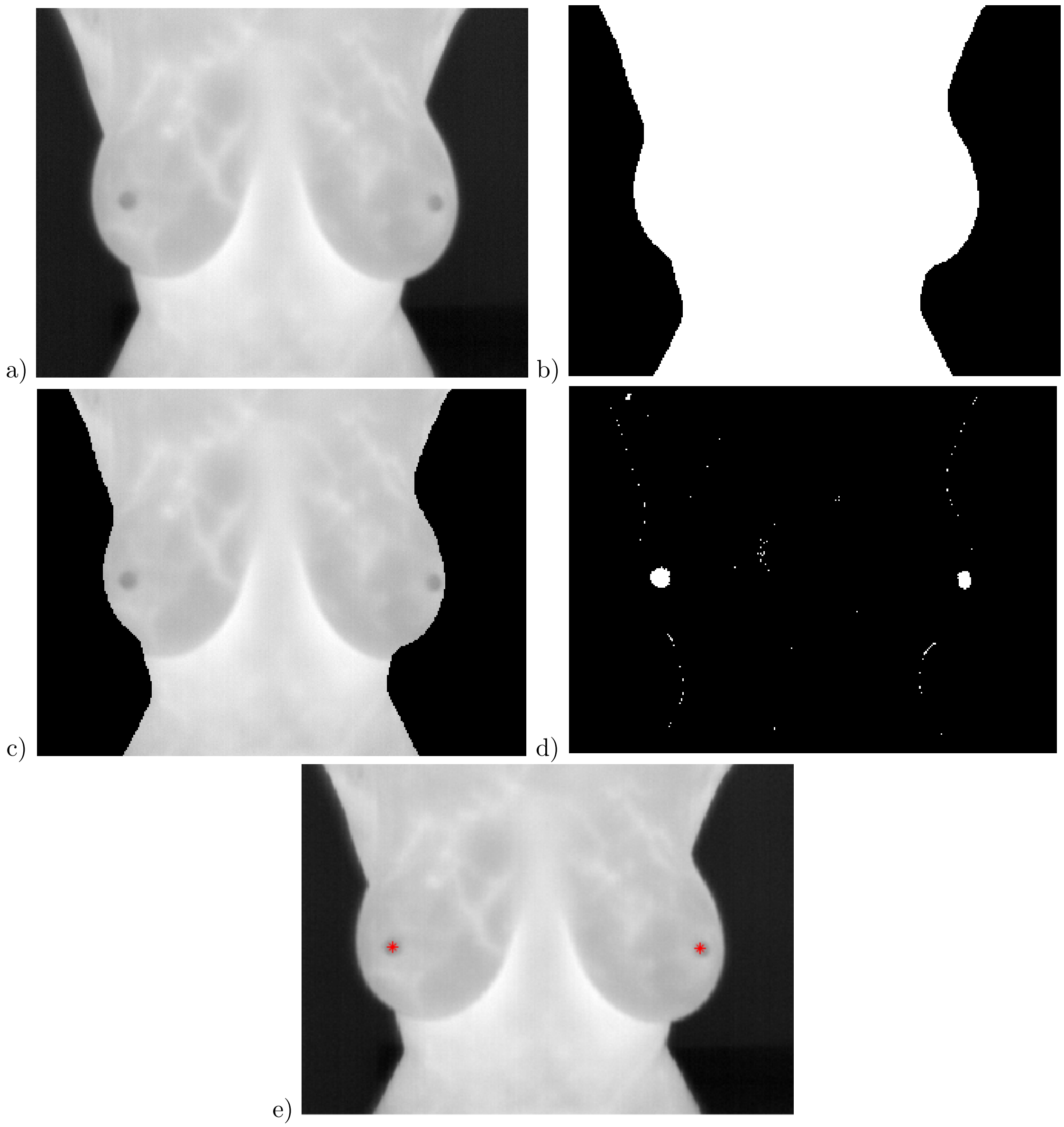


Figure 1: Output of each step of the algorithm: a) Input image b) Body mask c) Body segmentation using the mask d) Nipple candidates after adaptive thresholding and e) Original image with nipple locations overlaid.

**Nipple detection.** Finally, after determining the nipple candidates, a selection algorithm is applied in order to select the two final nipples. This is done in a series of steps: 1) the regions for each candidate are computed using a region growing algorithm that I implemented, which takes as input a binary matrix, and converts it to a non-binary matrix by labelling each pixel with a value 1 to a value corresponding to its selected region. The result, no 2 adjacent pixels will have different labels unless one is labelled as 0. 2) the image is divided into upper, middle, and lower sections, as the nipples are guaranteed to be located within the middle section. Therefore, each candidate region is checked and removed if any pixel within the region lies within the upper or lower sections of the image. The sections of the image are shown in figure 2. 3) following similar approach as done in step 2, any region that has a pixel outside of the human body is removed. 4) The candidates in the image are split into left and right candidates, by finding the center of the image, *Lcnt*. 5) For each of the left and right candidates, the nipple corresponding to that side of the image is found. This is done by calling the *compute_nipple* function.

The *compute_nipple* function begins by determining the area of each candidate nipple, and then removing all of the candidates whose area is less than 20 pixels. If none of the candidates have more than 20 pixels, than the largest one is selected as the nipple. If there is more than one candidate remaining, then the roundness of each candidate is computed using:

$$R = 4\pi A/P \tag{1}$$

where A is the area of the region (number of pixels), and P is the perimeter of the region. P is computed by finding the boundary of the set of points that form the region, then summing the distance between each consecutive point along the boundary. The region with the highest roundness value is selected to be the nipple. If there is a tie for the most round candidate, then the region with the greatest area among the final candidates is selected. If there is still a tie, then the region is chosen arbitrarily from among the remaining candidates.

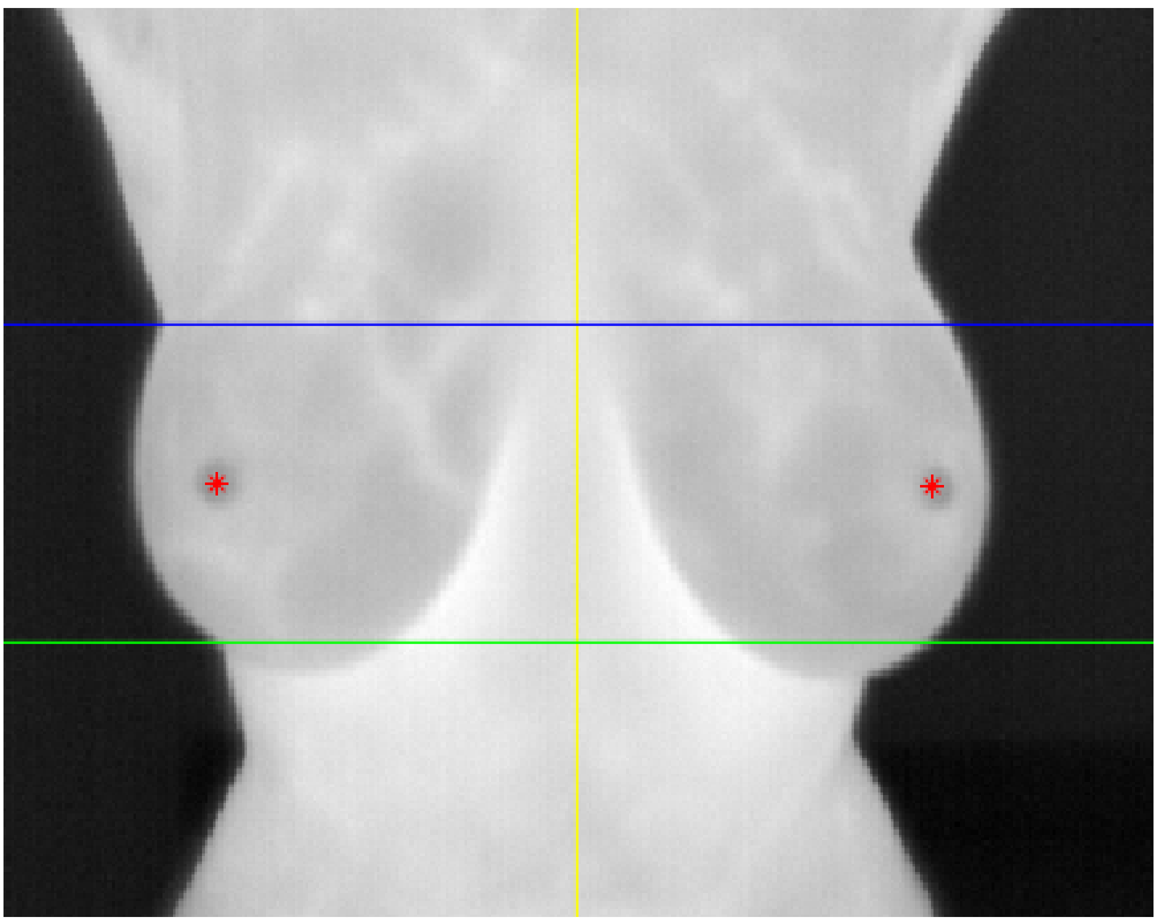

Figure 2: The sections of the image. The upper section, marked by a blue line, has a height of 0.35 * image height. The lower section, marked by a green line, has a height of 0.3 * image height. The center line, marked in yellow, is located directly in the center of the image, in order to divide the nipple candidates into left and right candidates.

Finally, the nipple coordinates are computed as the mean of all of the coordinates of the pixel corresponding to the selected region.

# 3 Results

In this section, I discuss the results of my implemented algorithm. I do this by analyzing both the precision, and the time requirements to compute the nipple locations. Six different images of breast thermograms were used to test my implemented algorithm. The results are shown in figure 3.

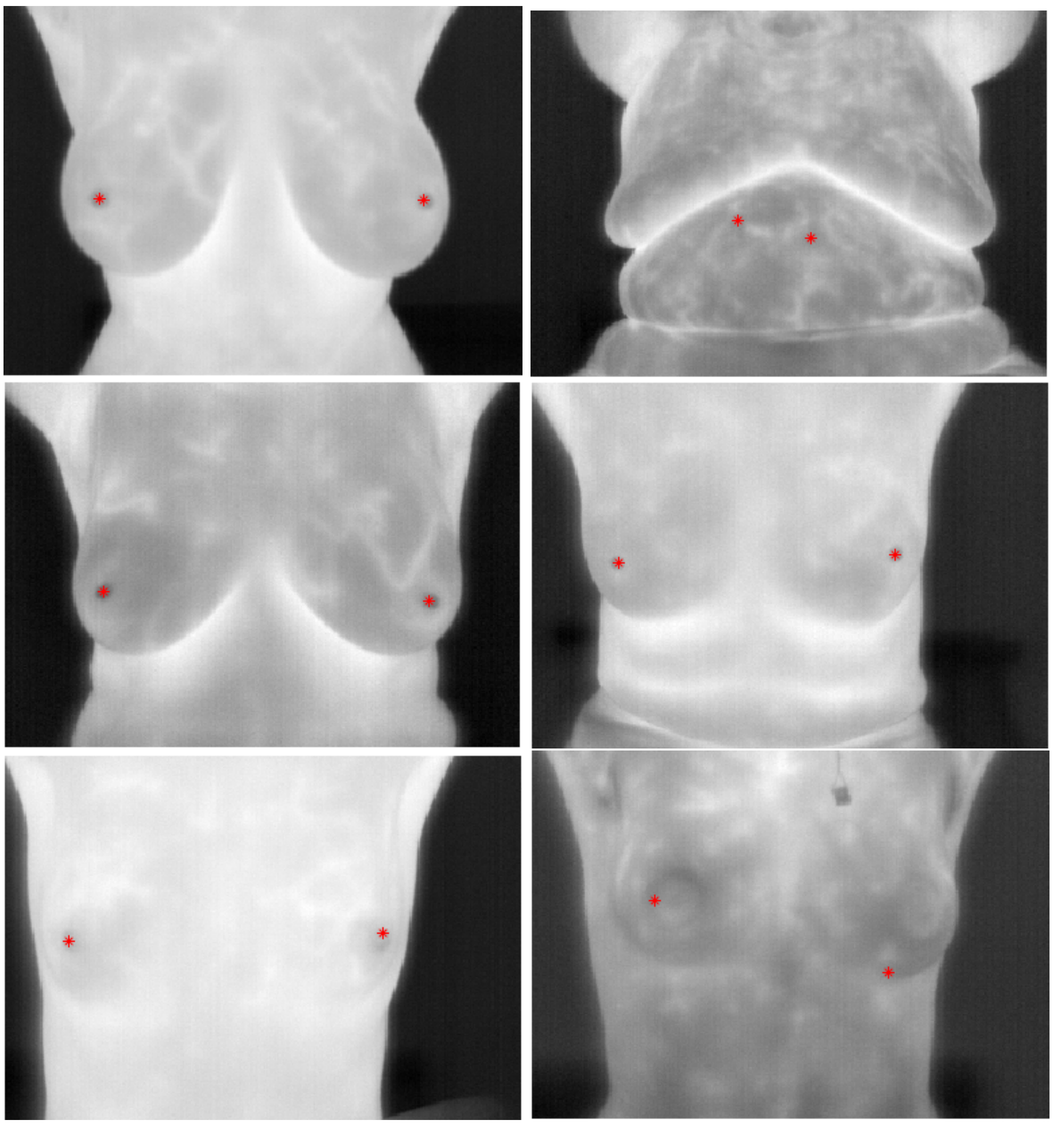

Figure 3: The results of the automatic nipple detection algorithm are shown here. The locations of the two detected nipples are shown for each test image in red overlaid on the original input image. The nipples in the 3 images on the left were correctly labelled, as well as the center image on the right. The nipples in the other two images were incorrectly labelled.

**Detection Capabilities.** As shown in the figure, the nipples in 4 of the 6 images were correctly located. This leads to 0.66 accuracy, or 0.4 precision. The four images that were correctly classified have more prominently showing nipples in the original image. The nipples in these images could be described as small, dark circles. Contrary, the nipples in the 2 images that were not correctly labelled are either invisible even for a human to locate, or are large circles that are difficult to distinguish from the rest of the body. Given this observation, it would seem that the algorithm is quite capable of finding nipples that are easily distinguishable from the human body, but lacks the capability to find nipples that have a smoother transition from the body to the nipple. Furthermore, this could be a result of the median filter that was applied. When applying this filter to a dark spot in the image where the neighbours are light, then the spot is more likely to change to an alternative color. Contrarily, when the nipple is shown lightly colored, similar to the rest of the body, then the median filter will not change the value of the pixels considerably.

**Computing Time.** The computer that was used to execute the algorithm has an Intel core i7-5500 processor that runs at 2.4GHz, and 8GB of RAM. Using this machine, after 6 trials on the same image, the average running time to compute the nipple locations was 0.16 seconds. This indicates that the algorithm implemented works extremely efficiently, which makes it practical to use in applications.

# 4 Conclusion

In conclusion, I implemented the automatic nipple detection algorithm presented by [1], and demonstrated the results. The algorithm works very well for thermogram images of breasts where the nipple is darker, and clearly visible. On the other hand, the algorithm does not perform well when the nipple is a similar color to the body (ie. hard to see), or completely not visible to the human eye. Furthermore, the algorithm is extremely efficient for time, making it usable in application.

# References

[1] Mohamed Abdel-Nasser et al. *Automatic nipple detection in breast thermograms*. 2016. DOI: https://doi.org/10.1016/j.eswa.2016.08.026. URL: http://www.sciencedirect.com/science/article/pii/S095741741630416X.