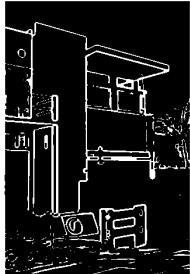
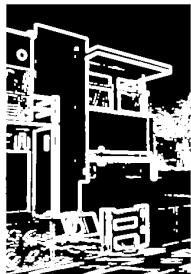


INFOIVB 2:Morphological Filters

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1. Comparison of images X, Y, and Z:

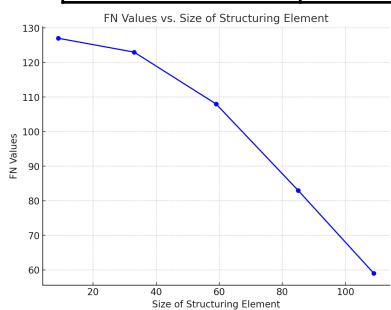


(X: dilate W with 3x3 kernel) (Y: erode W with 3x3 kernel) (Z: AND X and Y complement)

Image Z shows the difference between the dilated image X and the eroded image Y. Image Z is taken from the AND operation between image X and the complement of image Y. Image X expands the edge of the image, while image Y shrinks the edge. Then, inverts the eroded image Y to make it become the complement of Y. Finally, the AND operation keeps the pixels that are white in both images. In other words, image Z essentially highlights the edges of the original image W where dilation has significantly added new pixels, and erosion has removed them.

2. Distinct pixel values with various structuring element sizes on dilated images:

F1: 9x9, "square". Number of distinct values: 127.	F2: 33x33, "square". Number of distinct values: 123.	F3: 59x59, "square". Number of distinct values: 108.	F4: 85x85, "square". Number of distinct values: 83.	F5: 109x109, "square". Number of distinct values: 59.



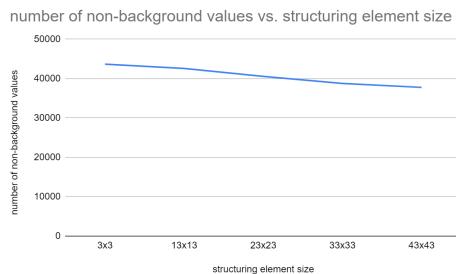
The graph above shows the trend, that is, as the structuring element size increases during a series of dilations on Image A, the number of distinct values for FN steadily decreases. Starting with a high number of distinct values for F1 of 127 for a small structuring element (9x9), the distinct values drop to 59 for a structure element size of 109x109. This occurs because dilation, especially with larger structuring elements, merges finer details and actually simplifies the image. Consequently, the image becomes more homogenous, reducing the number of distinct pixel values. The same input image is used for each subsequent dilation, and the increasing size of the structuring element directly leads to this reduction in complexity.

3. Openings with increasing structuring element size and number of non-background values:

G1: 3x3, "square"	G2: 13x13, "square"	G3: 23x23, "square"	G4: 33x33, "square"	G5: 43x43
H1: 43675	H2: 42575	H3: 40575	H4: 38775	H5: 37975

The above table shows the results of applying morphological openings with increasing square structuring element sizes. H_n in the last row represents the count of non-background pixels in each image. In other words, H indicates the number of foreground (white) pixels after each opening operation.

From the series of images, we observe that smaller foreground objects are removed as the structuring element size increases, while larger objects are preserved but gradually eroded. As the size increases further, even connected objects become disconnected. This process is continuous, meaning once the foreground is removed or eroded, it does not return as the structuring element size continues to grow. The graph below further visualises the change in the number of non-background values as the structuring element size in increments of 10.



From the graph, there is a notable steady decline in the number of non-background pixels as the structuring element size increases. This makes sense because the opening operation is erosion followed by dilation. The erosion step progressively removes smaller and thinner parts of objects, and the dilation step could not fully restore them. As a result, the image becomes simpler and more disconnected with each step. To conclude, the opening could simplify an image by removing a smaller structure, yet the main structure will also be affected if the size of the structure element is too large.

4. Choice Tasks

The first choice task is 3: returns the image with only the largest shape.

Another choice task is 2: noise removal using morphological operations like opening (erosion followed by dilation). This effectively eliminates high-frequency noise while preserving larger structures in an image. It relies on the size and shape of the structuring element for optimal results. Example of the noise removal is below, where opening was applied:

