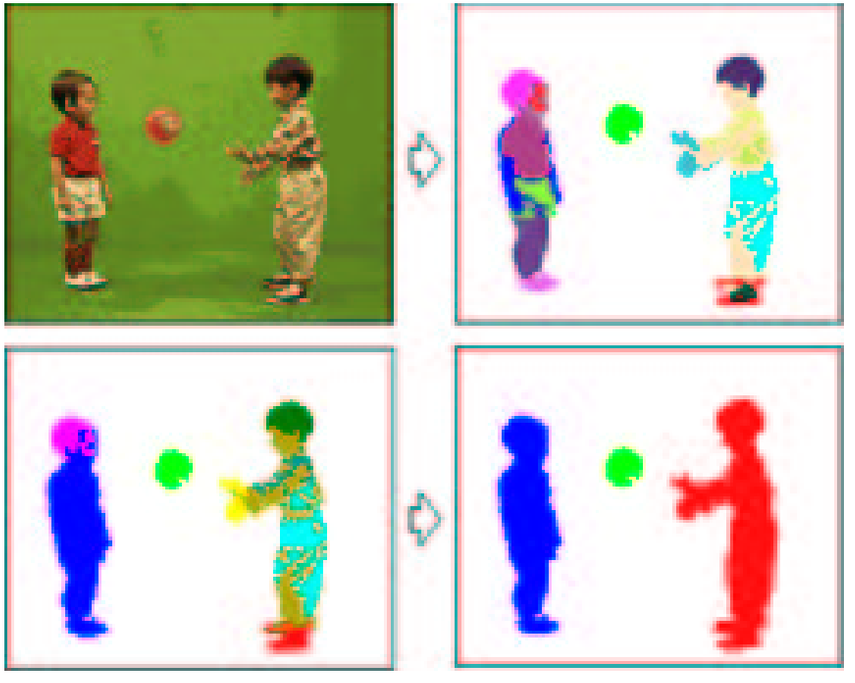
IMAGE SEGMENTATION

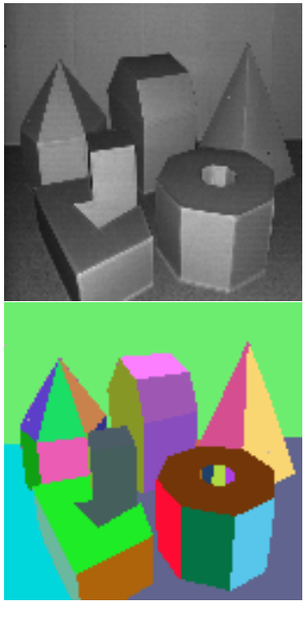
Ondřej Drbohlav, Václav Hlaváč, Jan Kybic

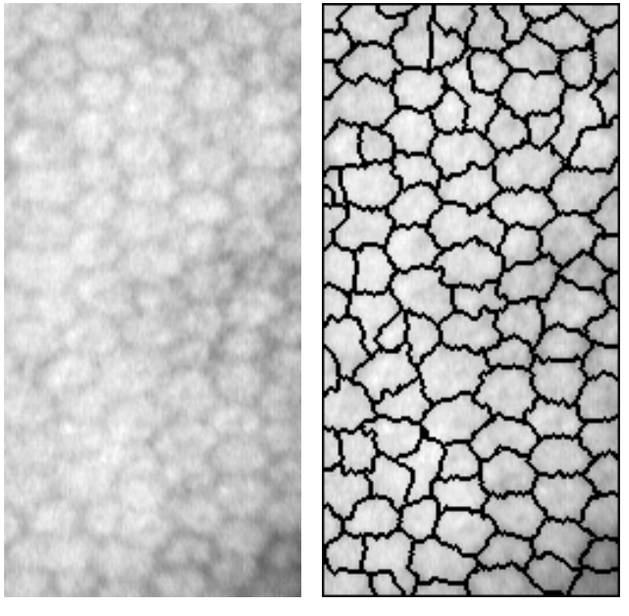
Czech Technical University, Faculty of Electrical Engineering
Department of Cybernetics, Center for Machine Perception
121 35 Praha 2, Karlovo nám. 13, Czech Republic

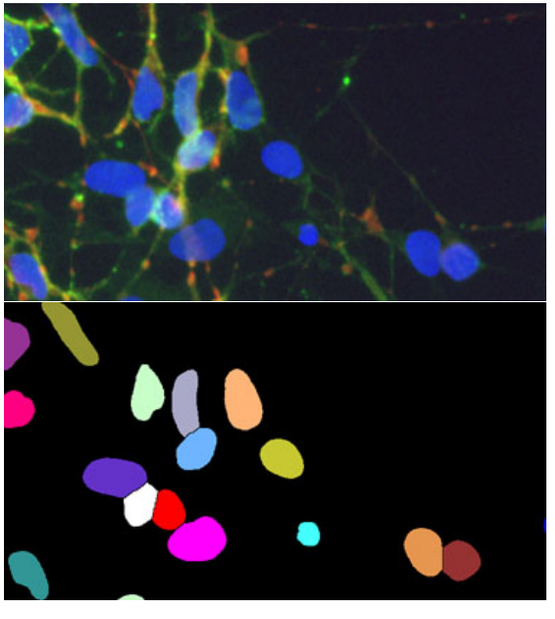
{drbohlav,hlavac,kybic}@fel.cvut.cz, http://cmp.felk.cvut.cz

WHAT IS IMAGE SEGMENTATION ?









IS SEGMENTATION EASY?

- What is easy for humans is generally not easy for computers. This is the case.

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Cells?

Cells are black.

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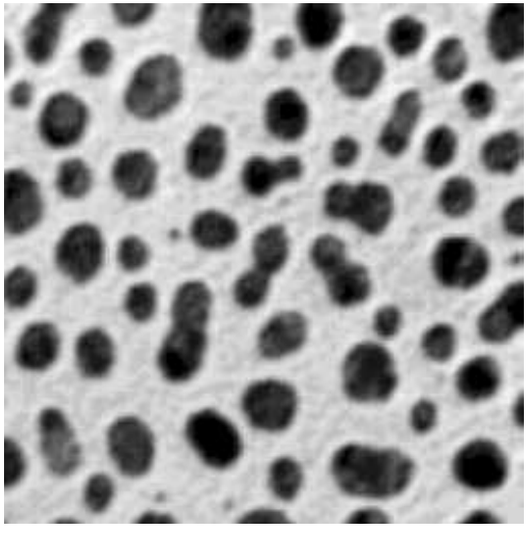

Cells?

Cells are homogeneous *connected regions*.

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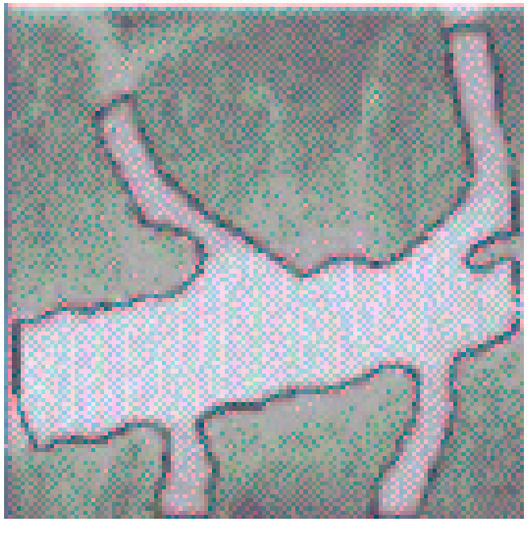

Artery?

Arteries are bright and *tend* to be elongated. They may have branches.

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Nose?

??? "I just see it".

THRESHOLDING

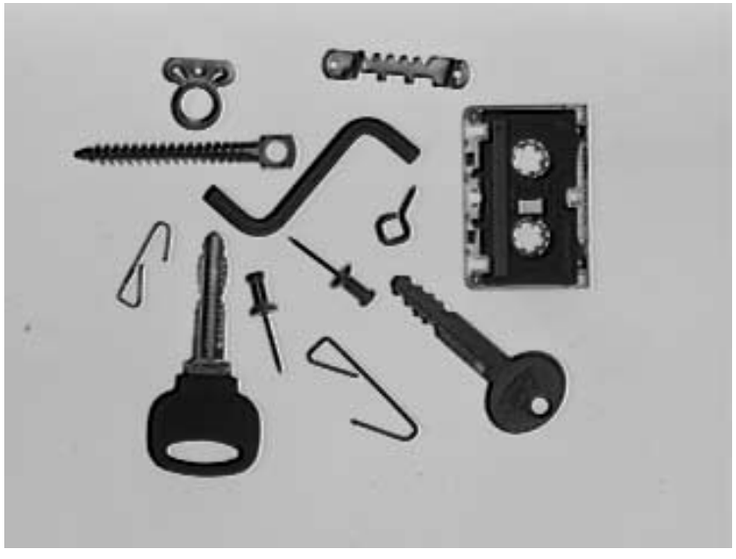
THRESHOLDING

- pixel is labeled to belong to object based on its intensity:
  - intensity higher than threshold $\Rightarrow$ object
  - intensity lower than threshold $\Rightarrow$ background

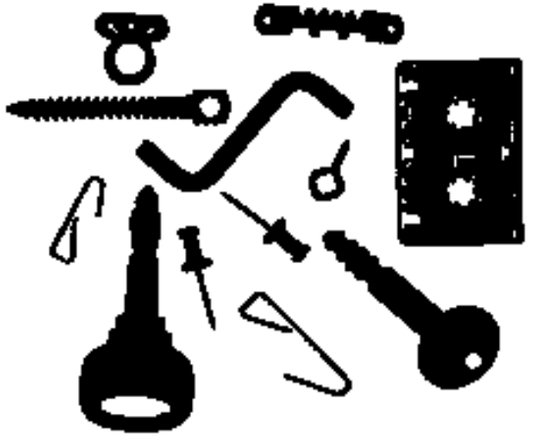
\+ Simplest algorithm hardly exists.

– Works only for subclass of images in which objects are distinct from background in intensity.

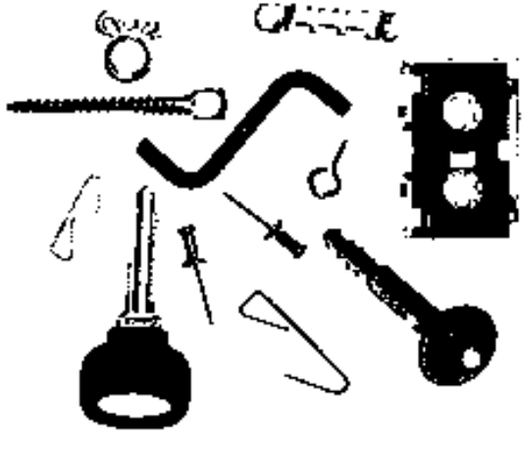
DEPENDENCY ON THRESHOLD SELECTION



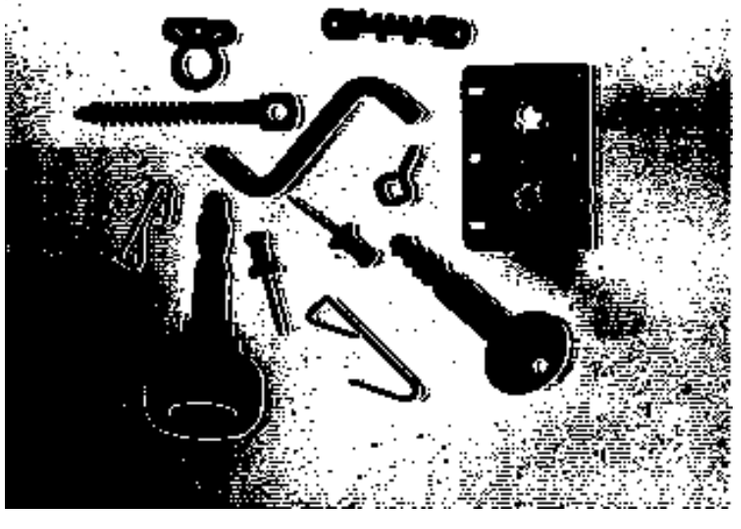
Original image.



Properly set threshold.

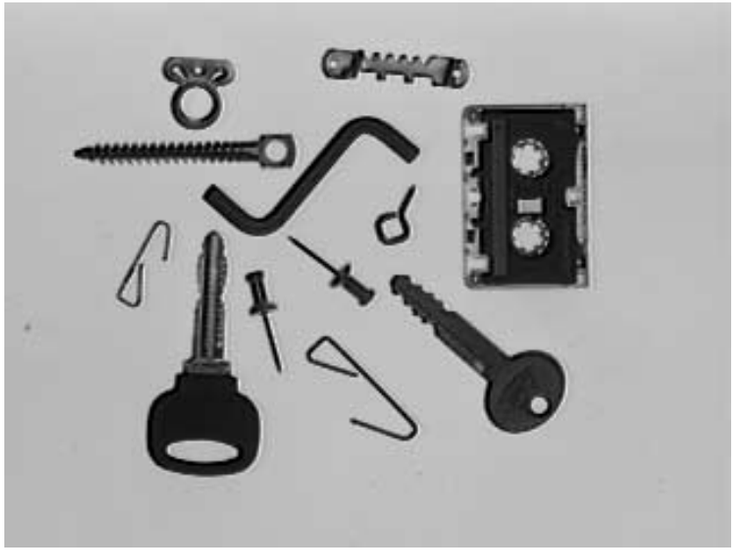


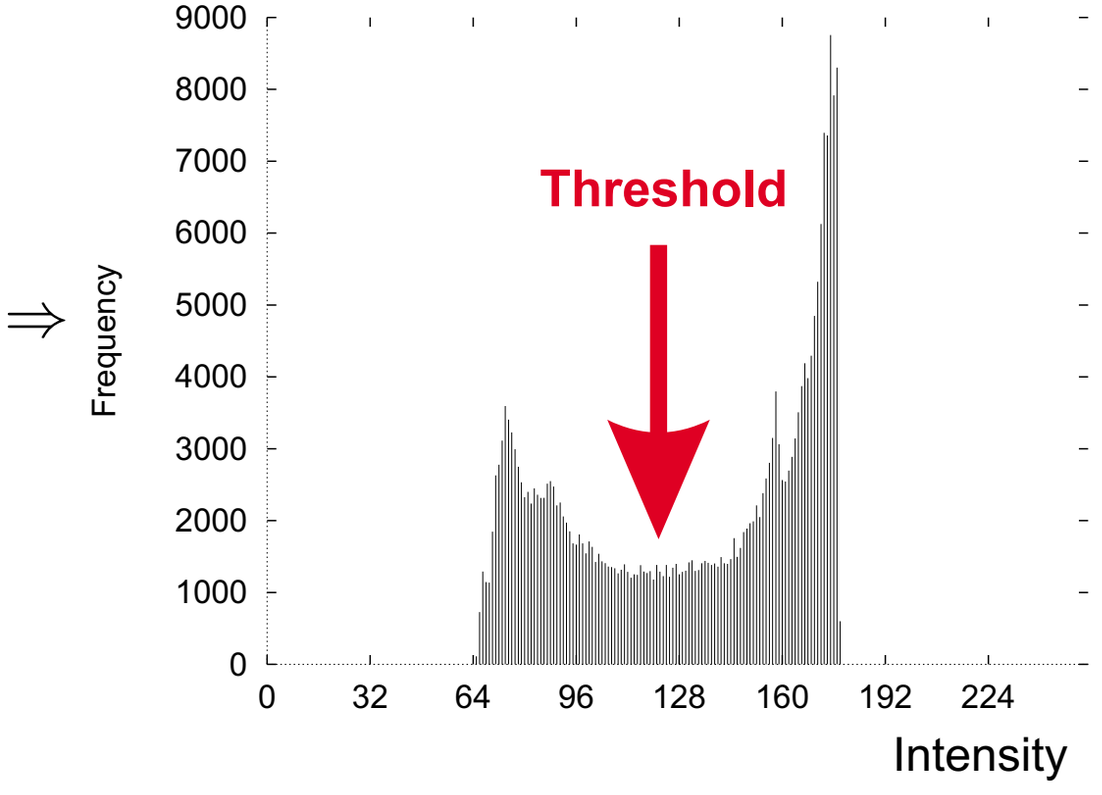
Threshold too low.



Threshold too high.

AUTOMATIC THRESHOLD DETECTION BY HISTOGRAM ANALYSIS





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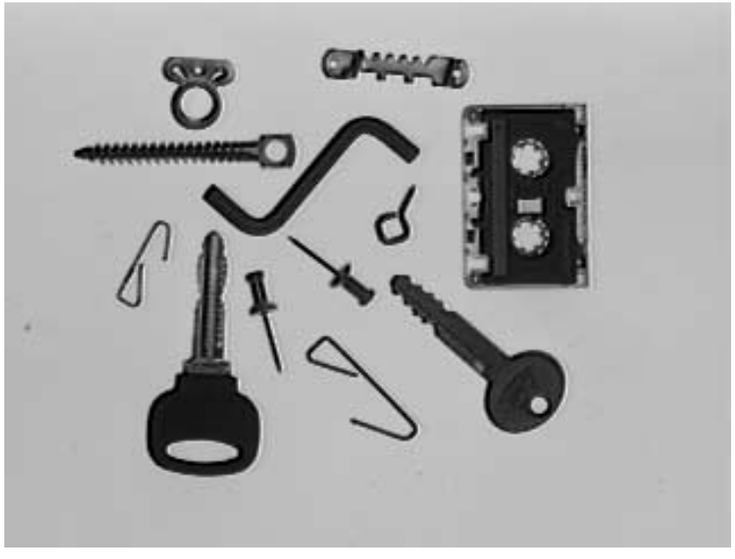
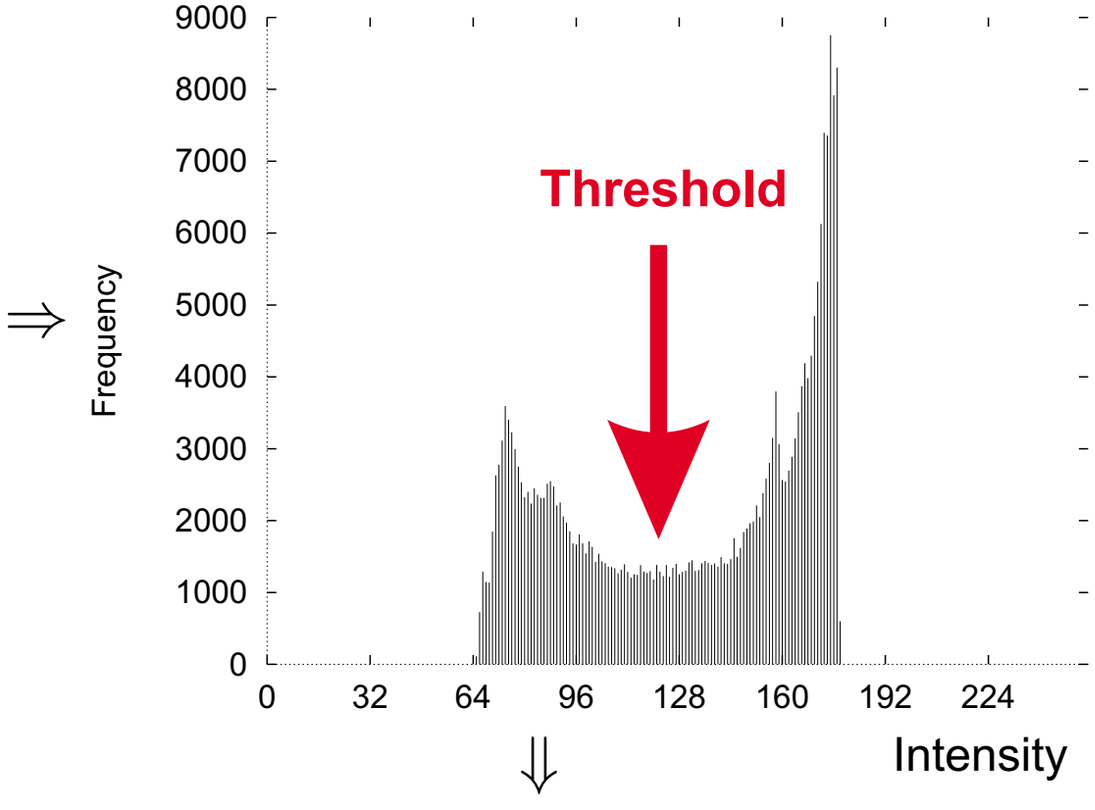
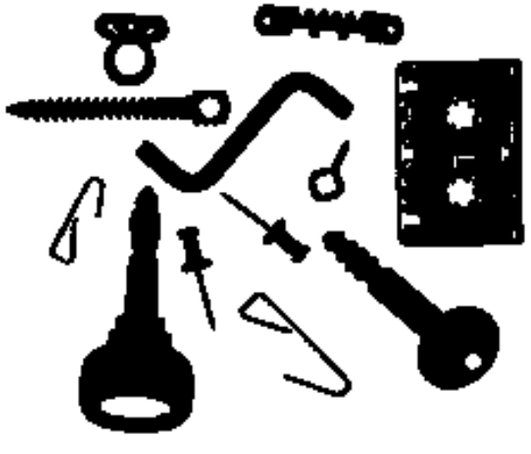


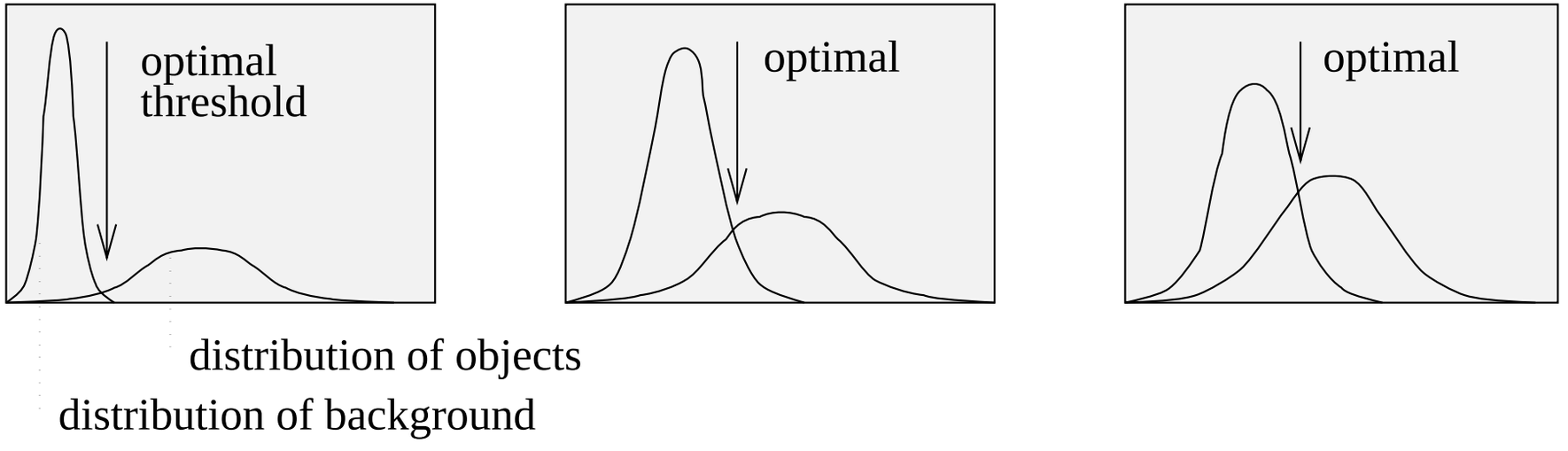




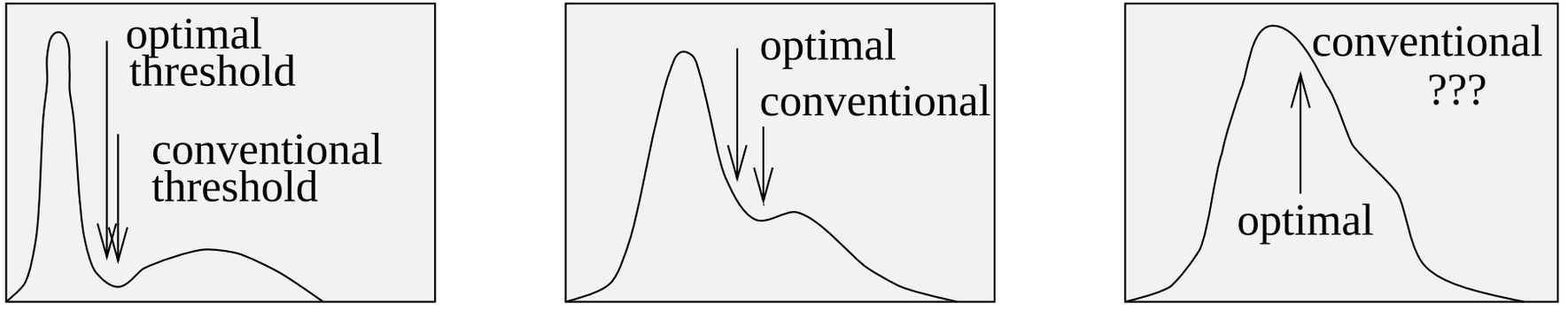
OPTIMAL THRESHOLDING BY MIXTURE OF GAUSSIANS

Motivation:

(a)



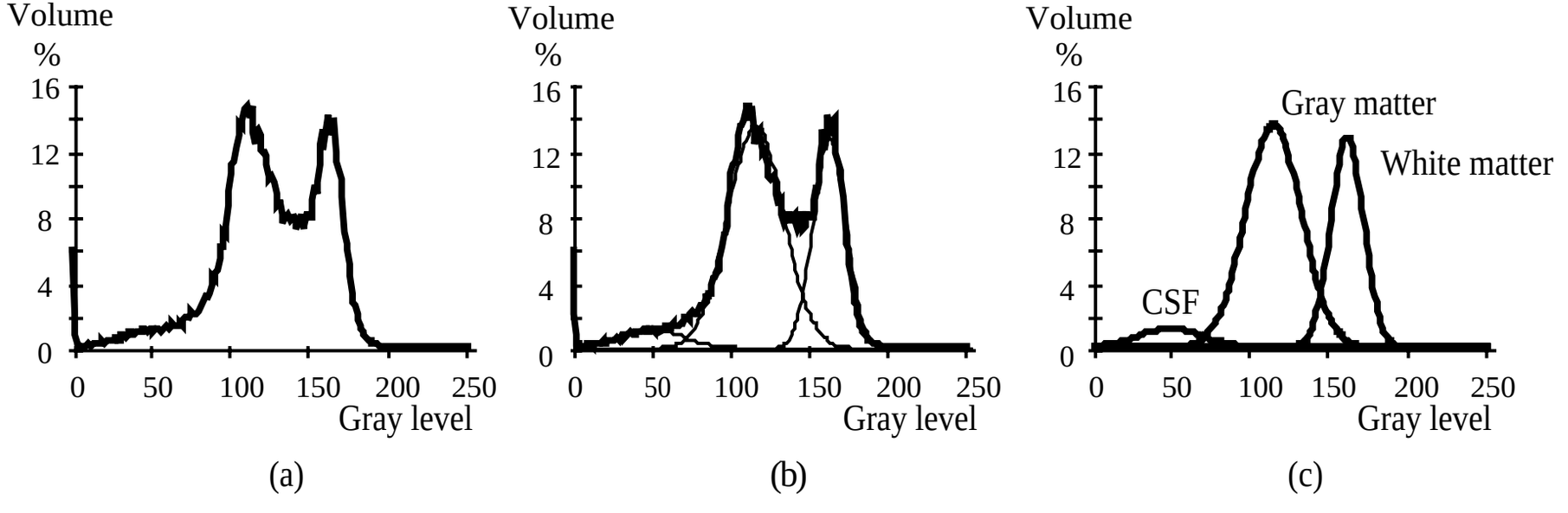
(b)



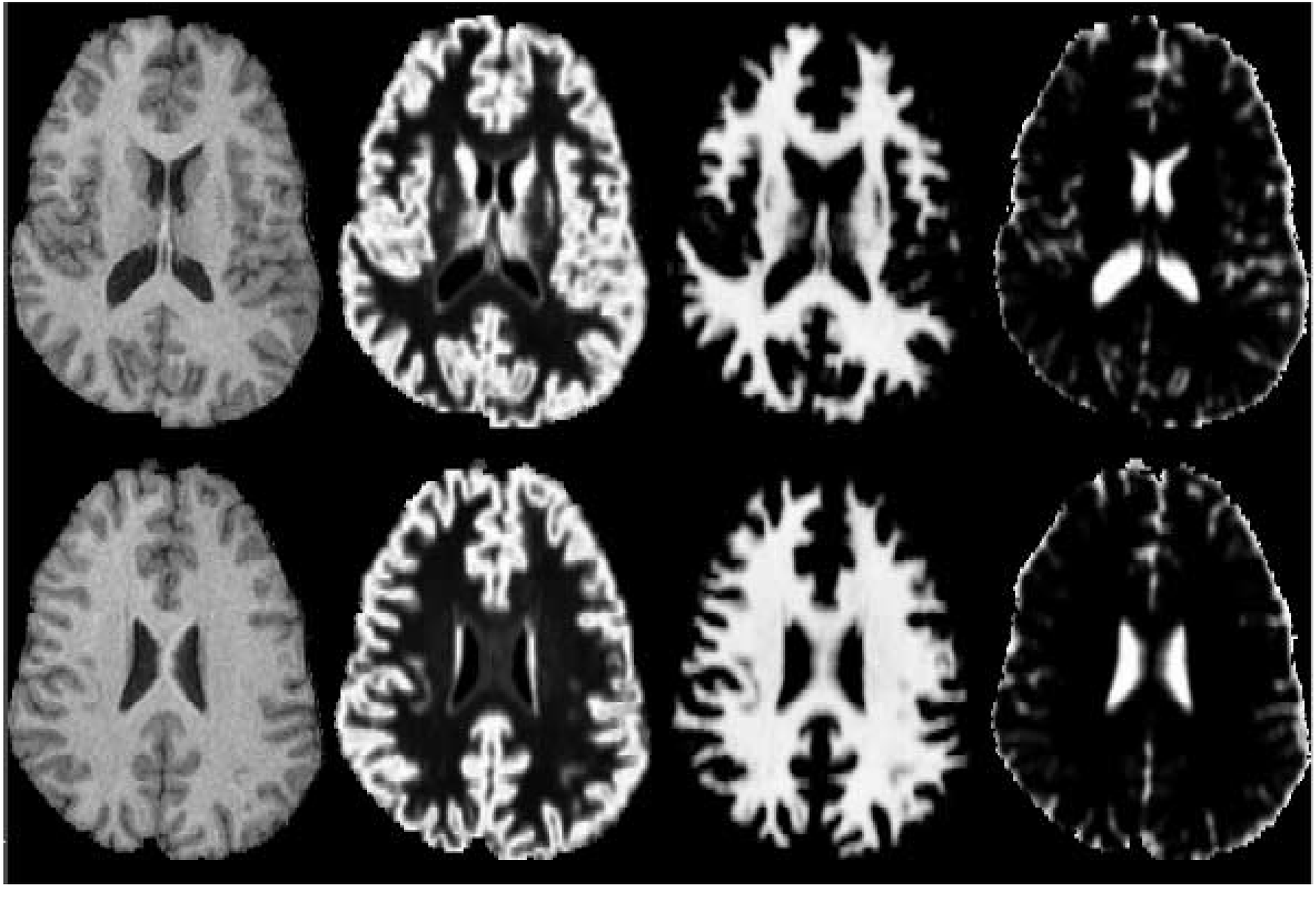
EXAMPLE, SEGMENTATION OF THE BRAIN MRI

Input: T1-weighted NMR images.

Desired classes: white matter, grey matter, celebro-spinal fluid (CSF)

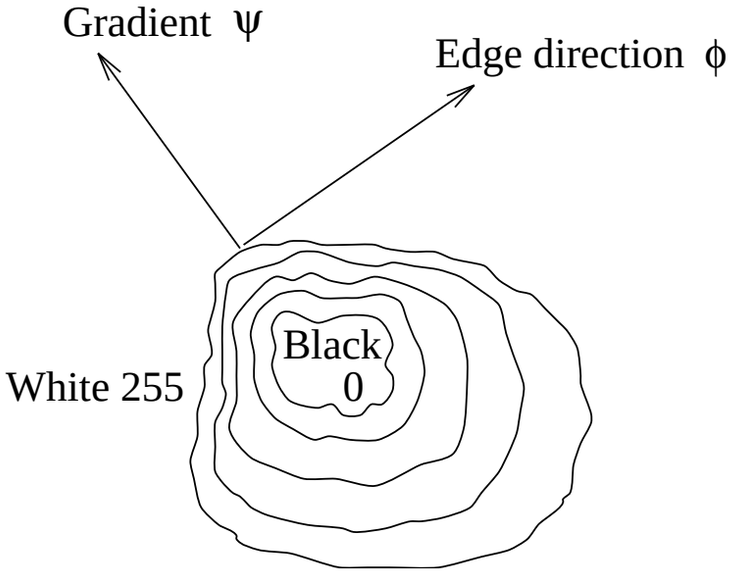


BRAIN MRI, SEGMENTATION RESULT



EDGE-BASED SEGMENTATION

WHAT IS AN EDGE?

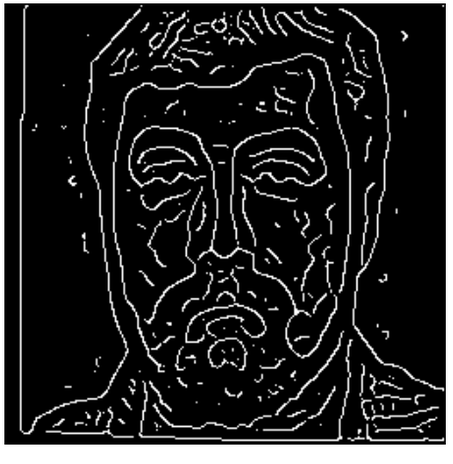


- vector attached to each pixel
- it has the direction of iso-intensity contour
- its magnitude is proportional to the steepness of image intensity in the pixel neighbourhood

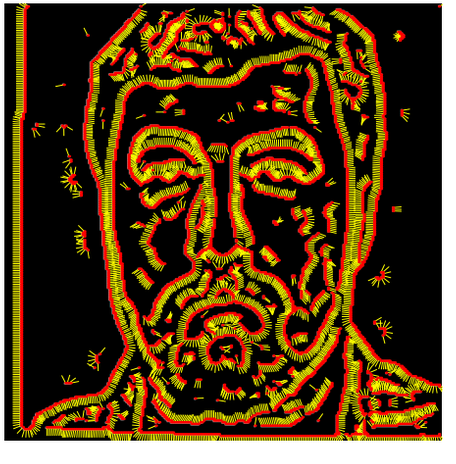
EDGES: EXAMPLE

Original image.

Edge magnitude.



Non-maximal suppression.



Nonmax + gradient direction.

HOW CAN EDGES HELP?

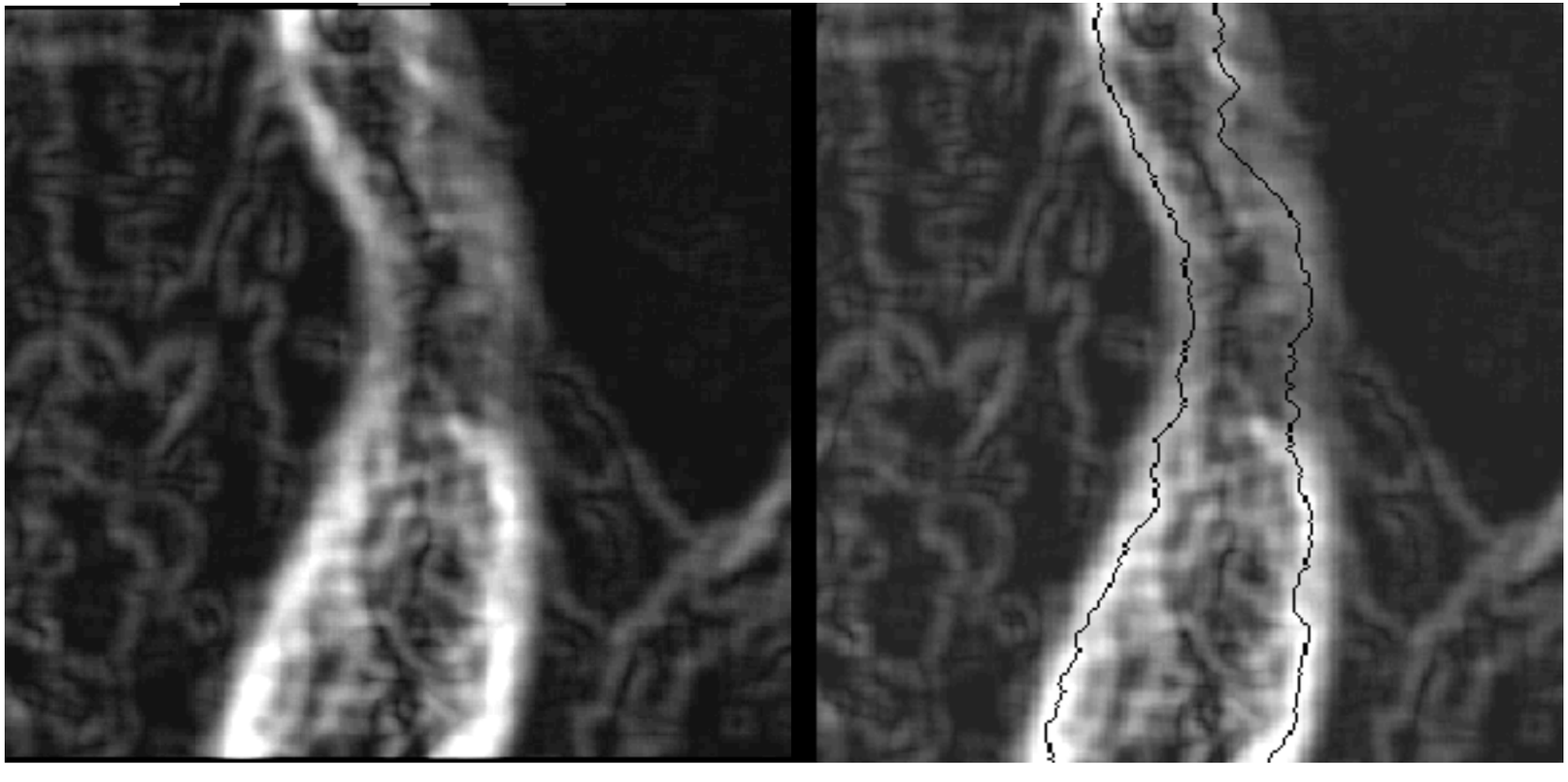
Facts:

- edges have high magnitude where changes in intensity are high
- they point in direction of zero intensity change

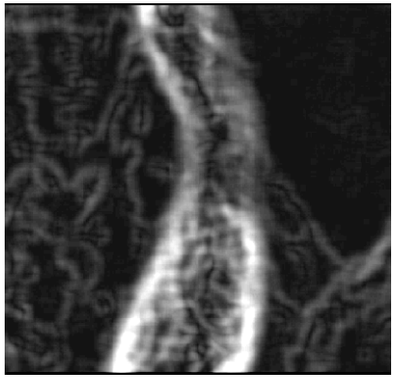
Implication:

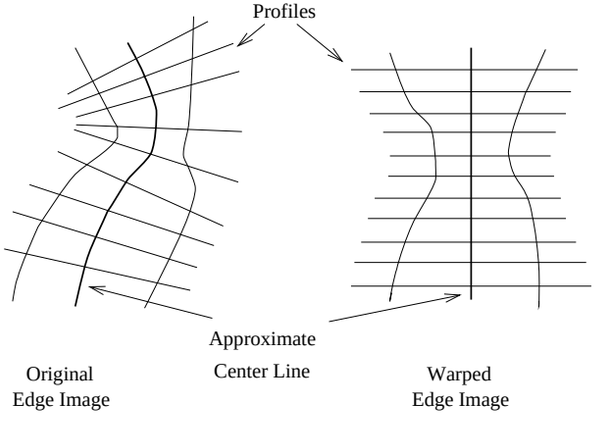
- edges can serve as fragments of boundaries between regions
- tracing edges may recover these boundaries

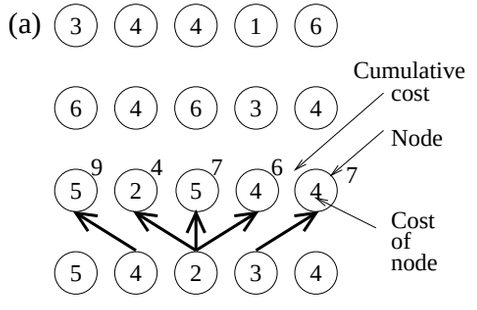
HOW CAN EDGES HELP? EXAMPLE

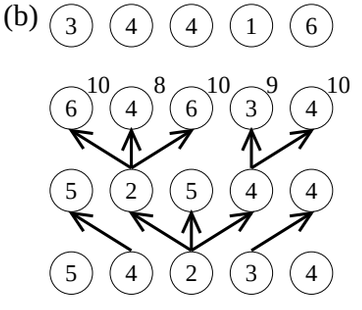


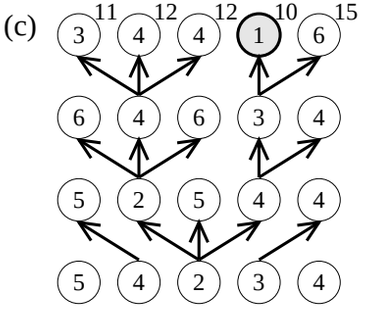
Segmentation: GRAPH SEARCHING

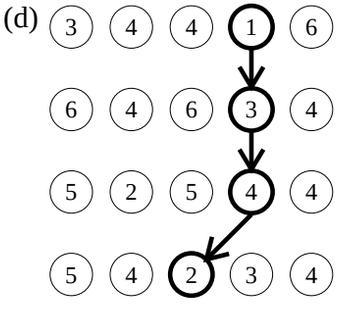












REGION-BASED SEGMENTATION

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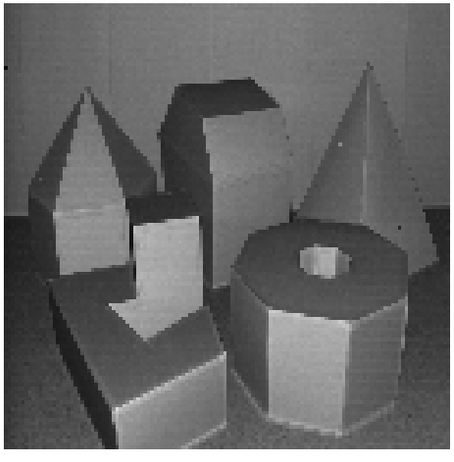
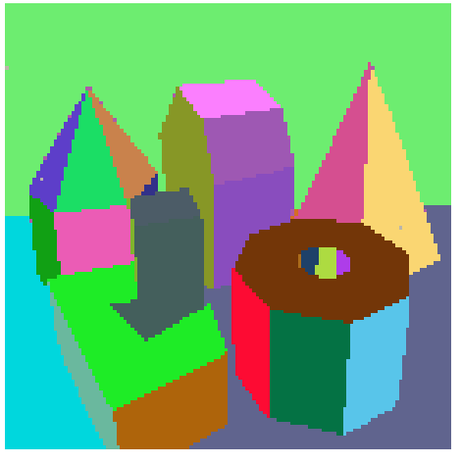
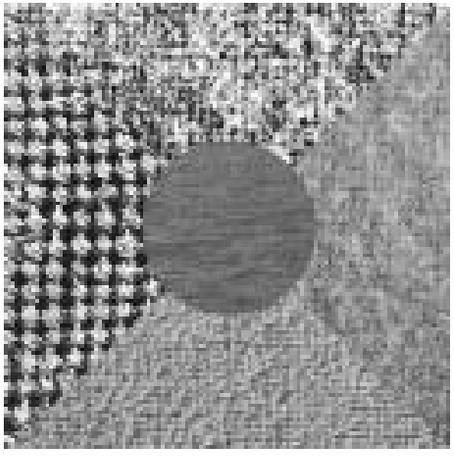
- relies on homogeneity of regions with respect to certain property
- property (ex.): texture, intensity, color


REGION-BASED SEGMENTATION

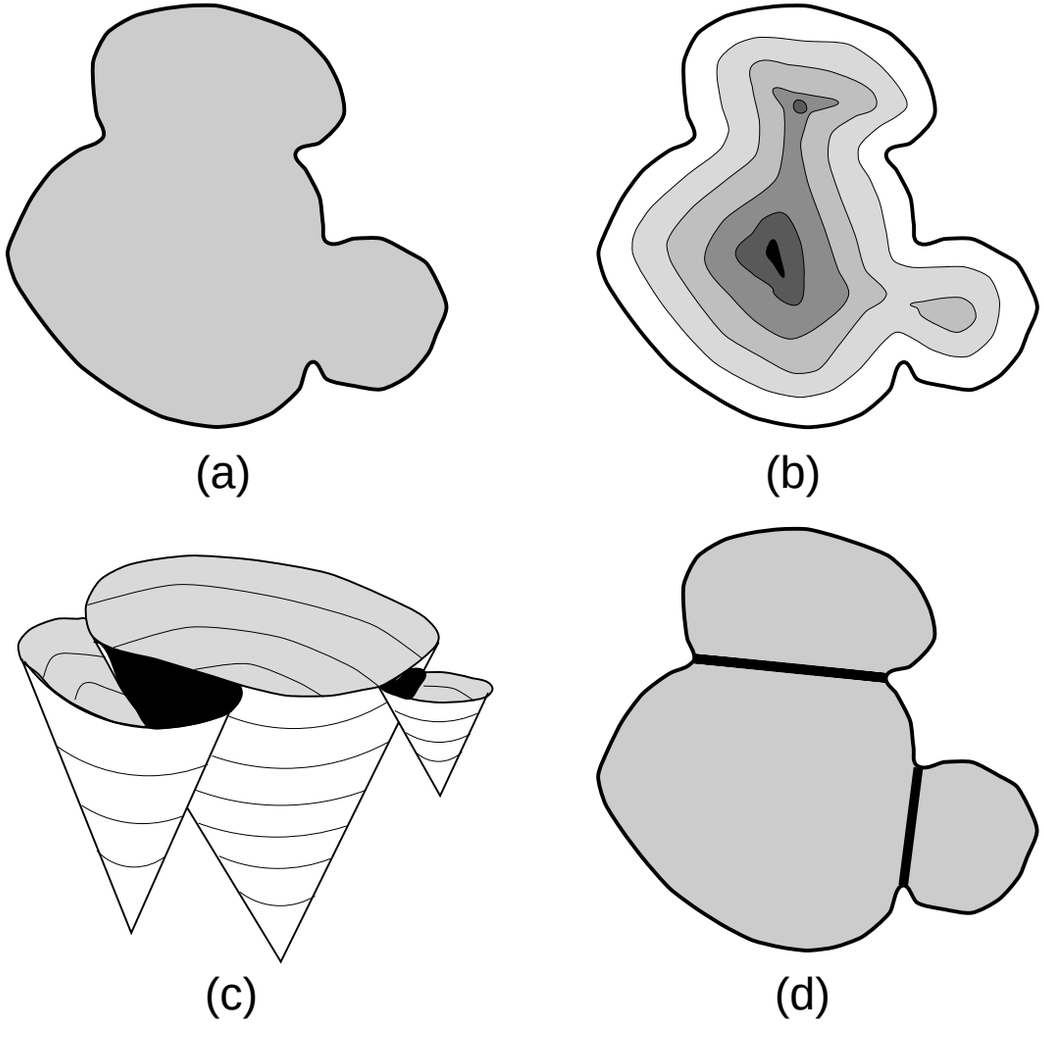
Possible strategies for extracting regions:

- region growing
- hierarchical image splitting
- watershed segmentation
- . . .

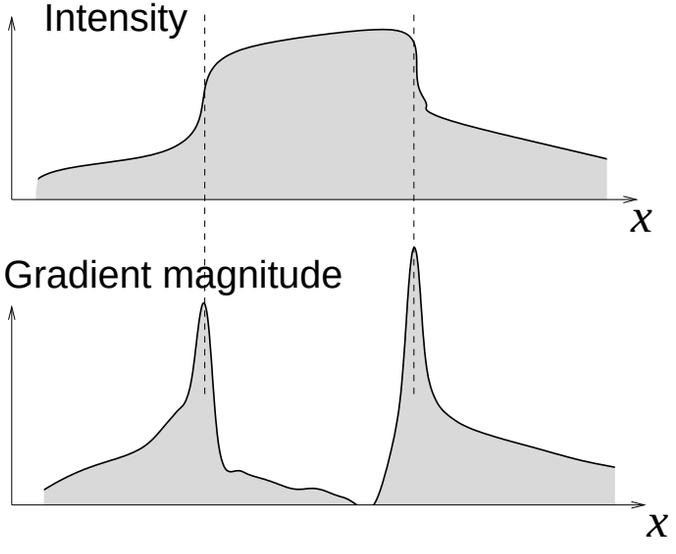
The region-based segmentation can be seen as complementary to the edge-based one.

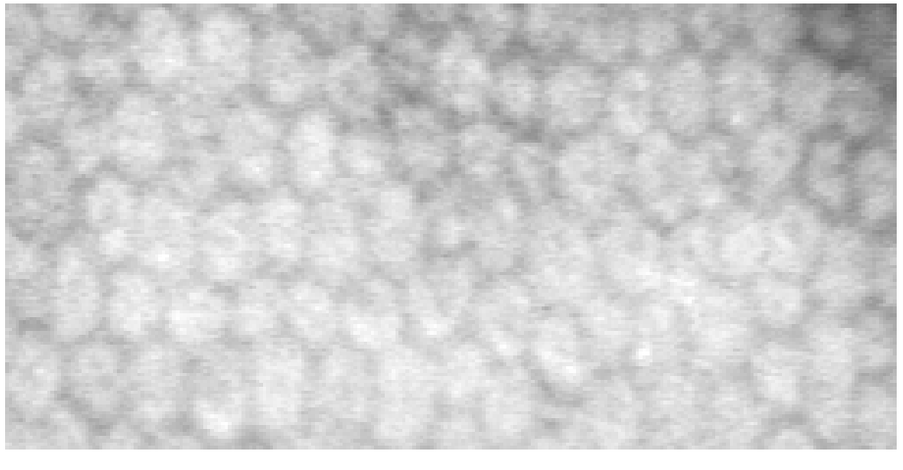
Segmentation of particles

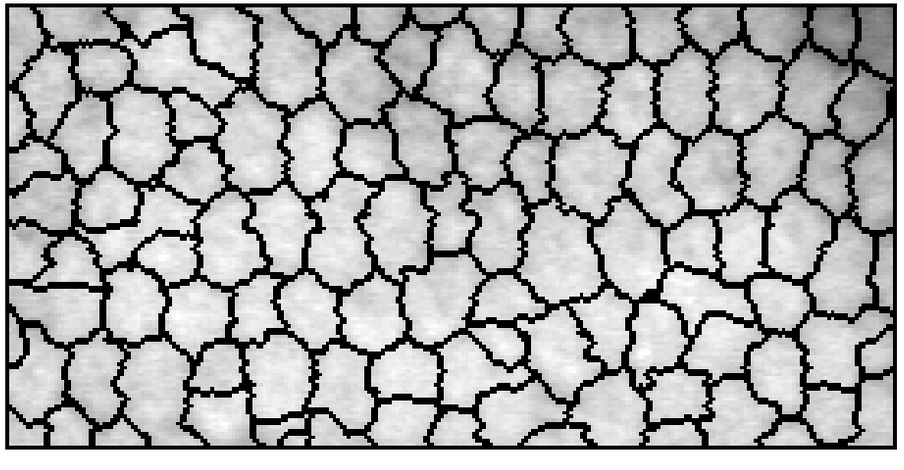
(a) input binary image, (b) distance function, (c) topographic image of catchment basins, (d) watershed segmentation



Segmentation of cells (gray-scale image)







ACTIVE CONTOURS/SNAKES

(Data/lecture_snakes_sonka.html)

(~/teaching/dzo/resources/lecture_snakes_lundervold.pdf)

(~/teaching/dzo/resources/snakes)

LEVEL-SET BASED SEGMENTATION

Dynamically evolving boundary:

- the boundary is initiated as a small circle
- it is evolved with normal speed inversely proportional to gradient magnitude

$\Rightarrow$ Video

```
mplayer -fs Movieartery.mpeg
```

HOUGH TRANSFORM

HOUGH TRANSFORM

- knowledge about the object shape is used
- voting into space of object shape parameters

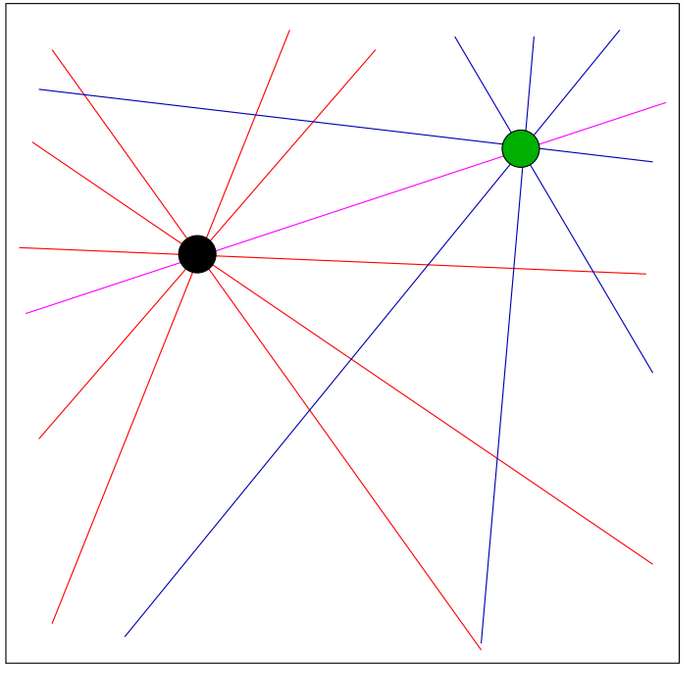
Example: Lines

(x, y) point in an image

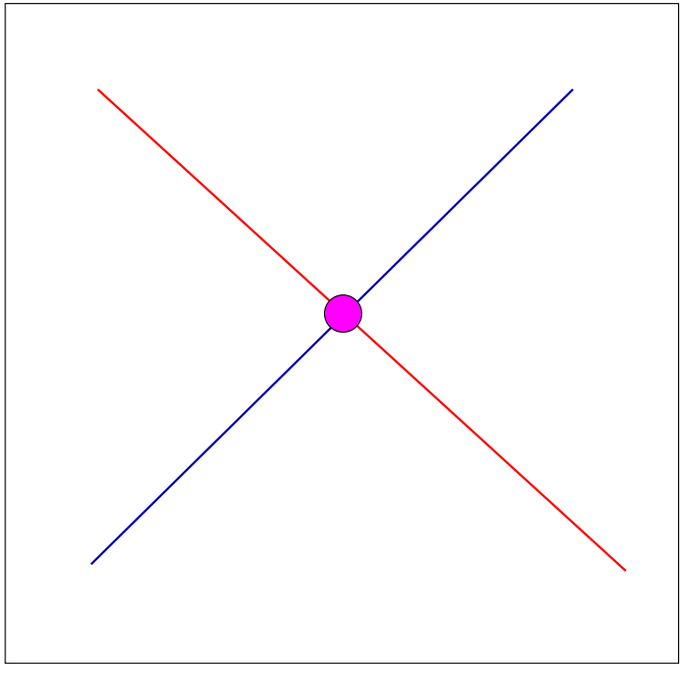
(k, q) line parameters

$$y = kx + q$$

(x,y) space

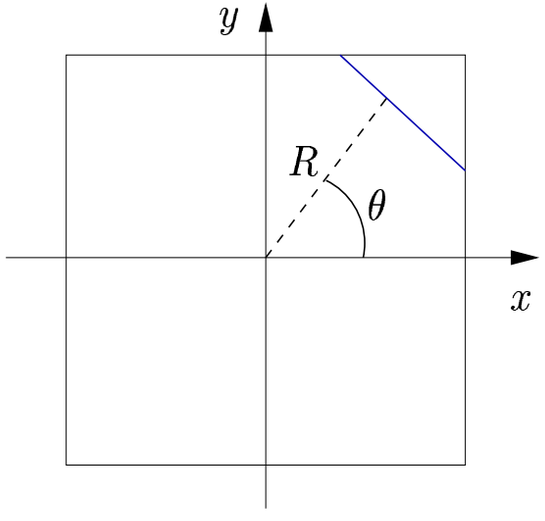


(k,q) space



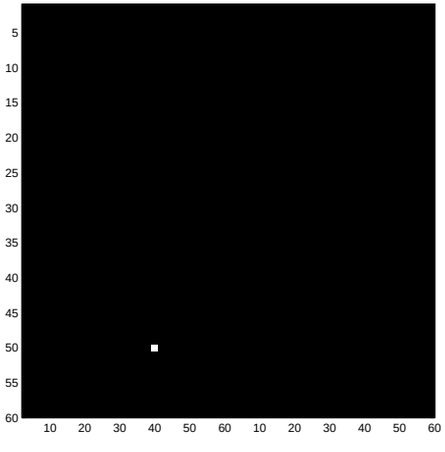
HOUGH TRANSFORM

Better parametrisation:

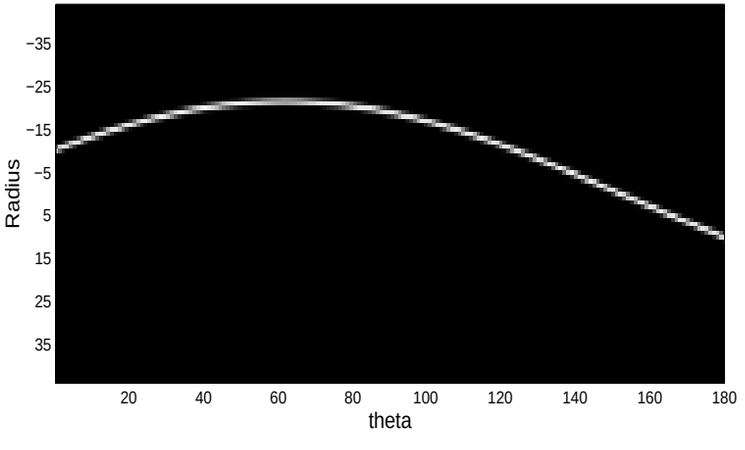


$$x\cos\theta + y\sin\theta + R = 0$$

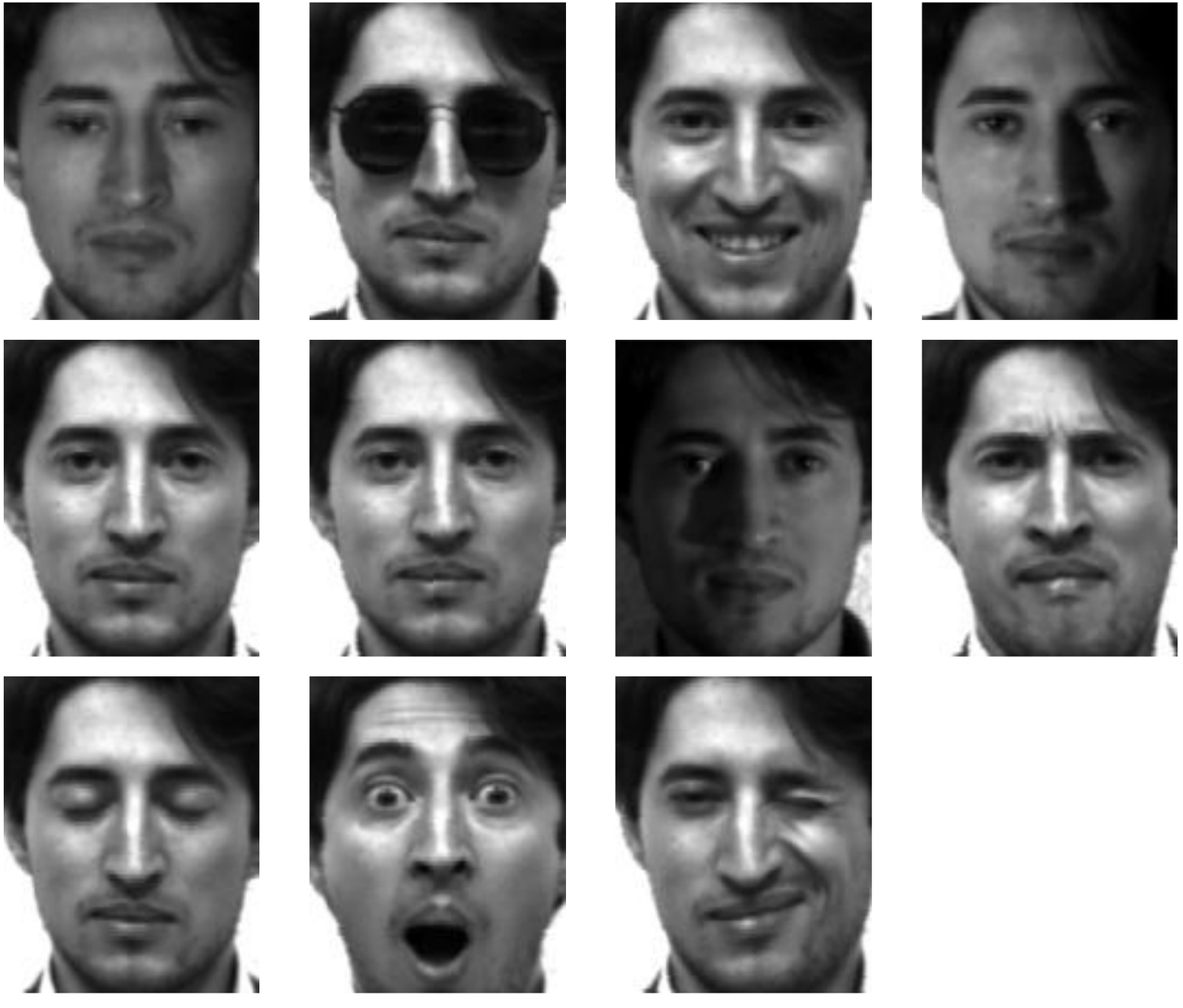
(x, y) space



(θ, R) space



HARDER PROBLEMS



HARDER PROBLEMS: SOLUTION STRATEGIES

- formulation of additional constraints
  - topological constraints
  - shape constraints
  - . . .
- sample-based methods $\Rightarrow$ recognition techniques
  - neural networks
  - PCA, LDA
  - . . .

Typically, identification of local features is not possible without global image interpretation.

Matlab demo

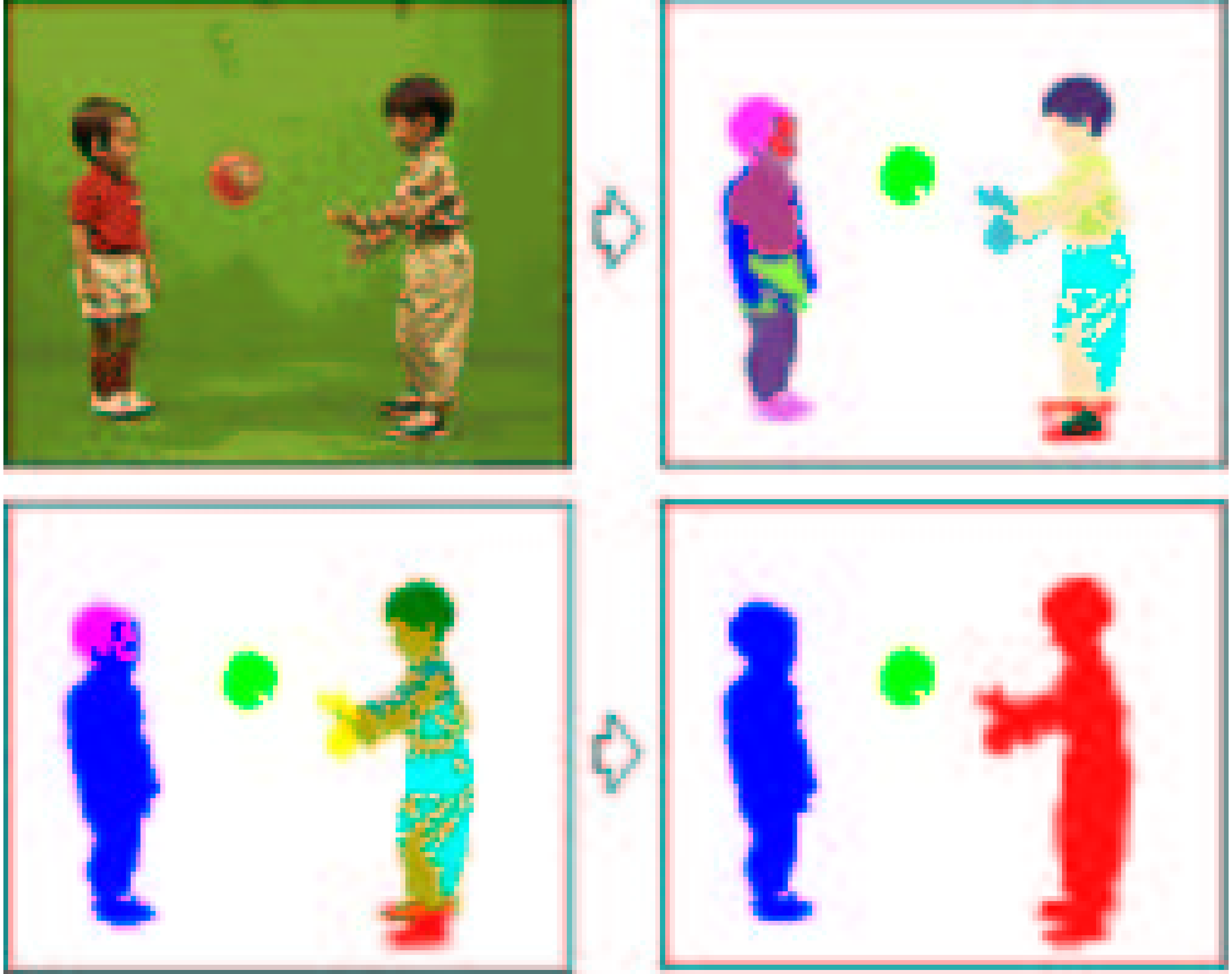
```
>> ipexsegcell
>> ipexsegmicro
>> ipexsegwatershed
```

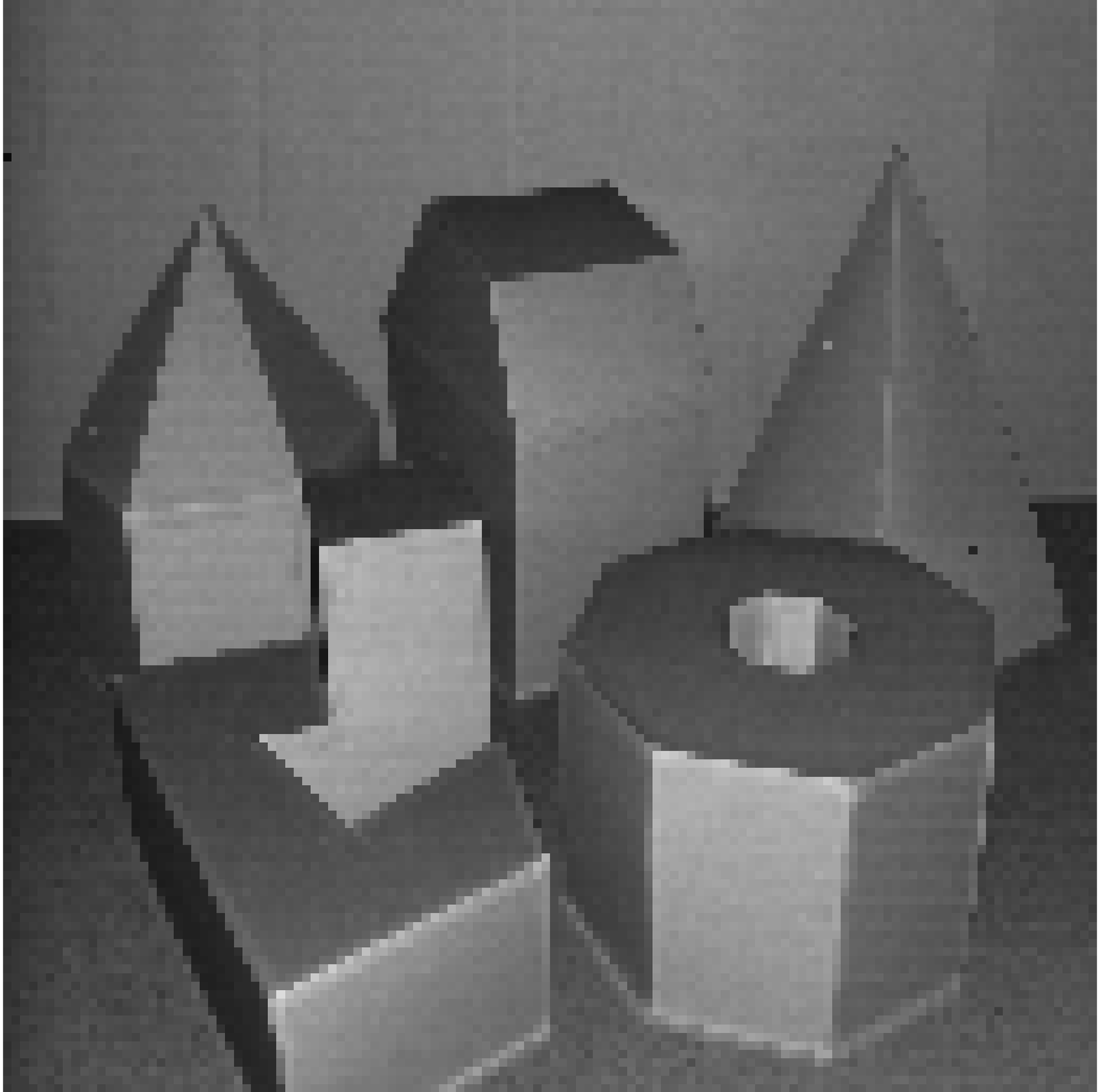
SUMMARY

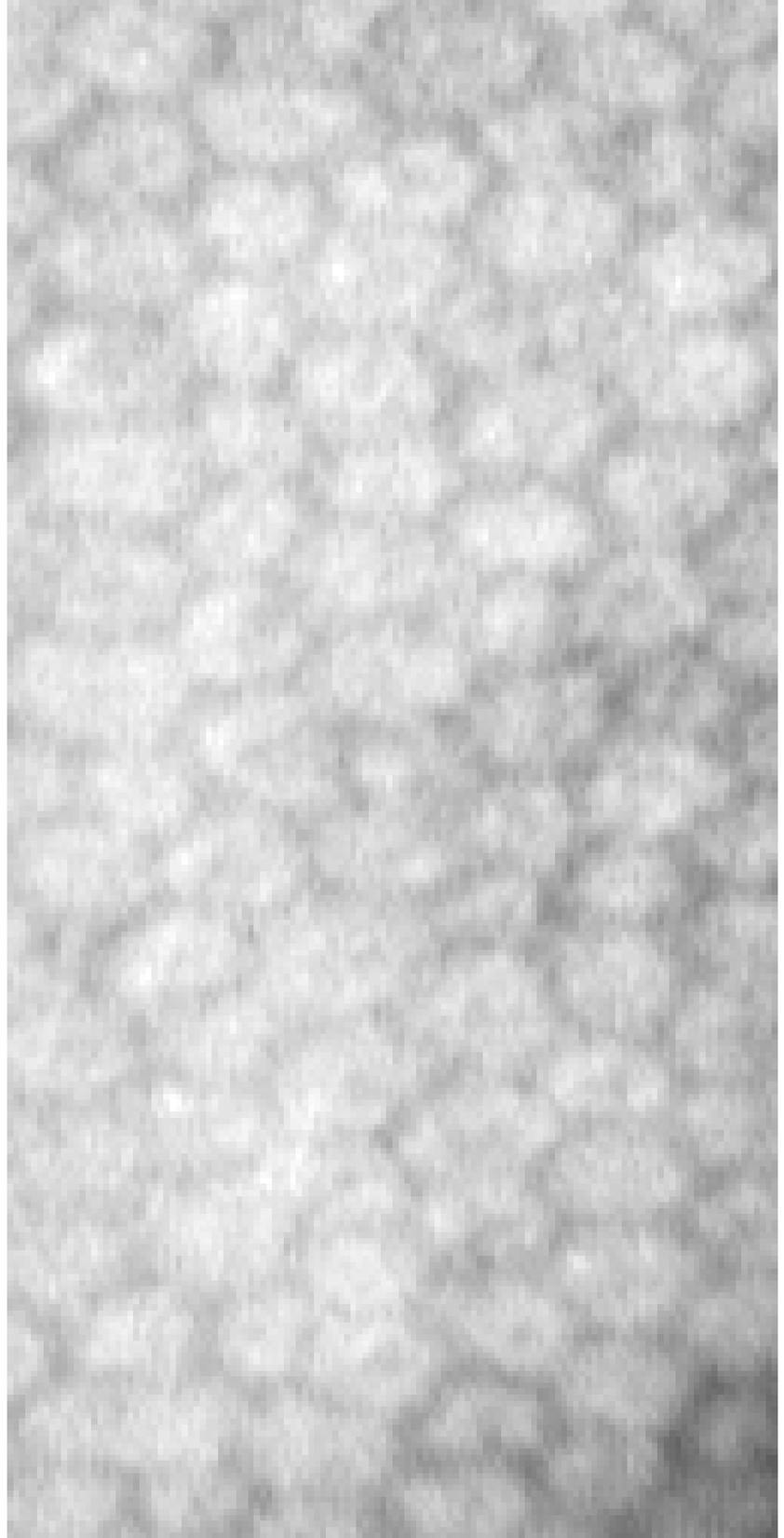
- segmentation finds objects of interest in the image
- the algorithm is highly dependent on the task to be solved

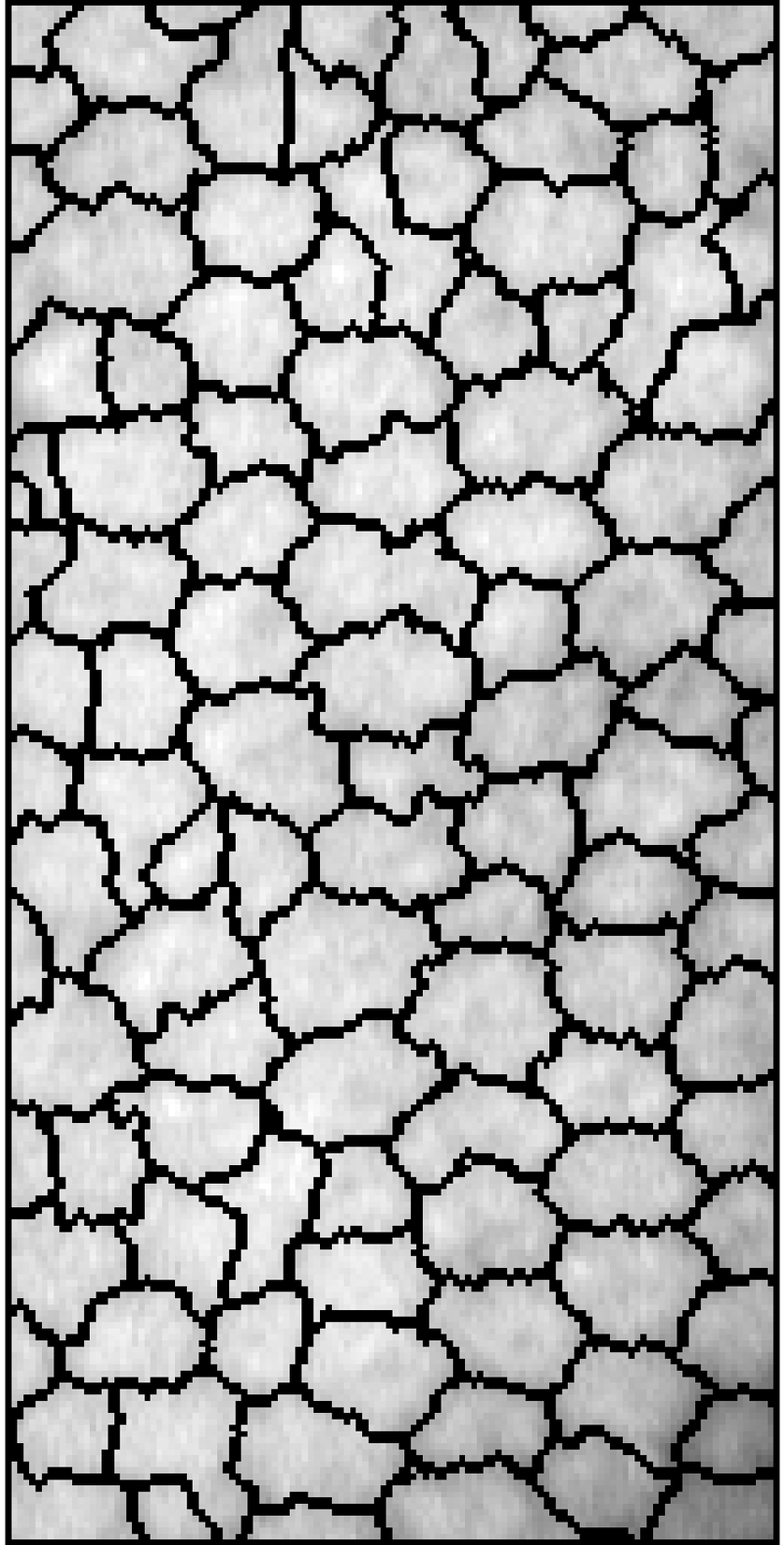
. . . thank you!

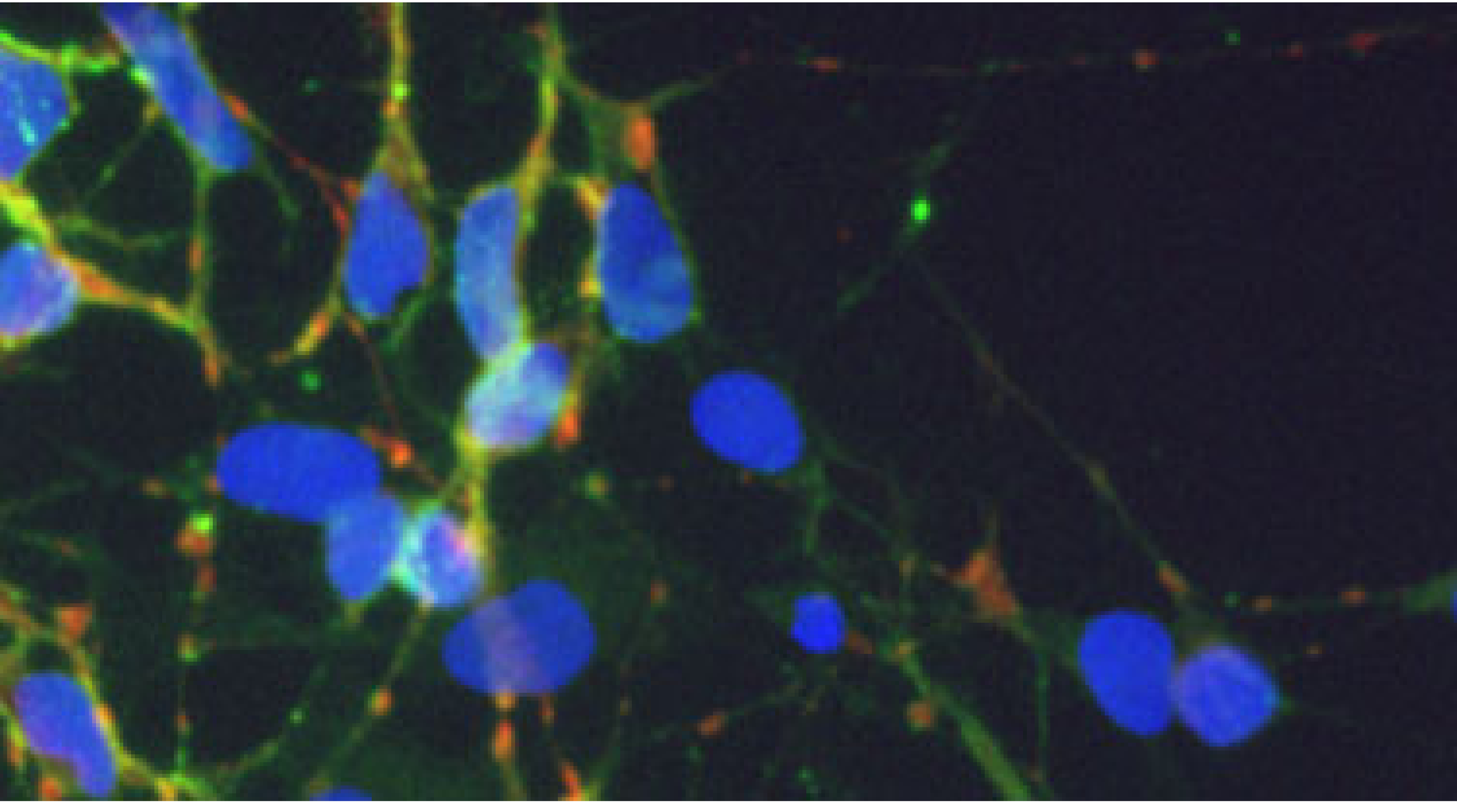

(c)

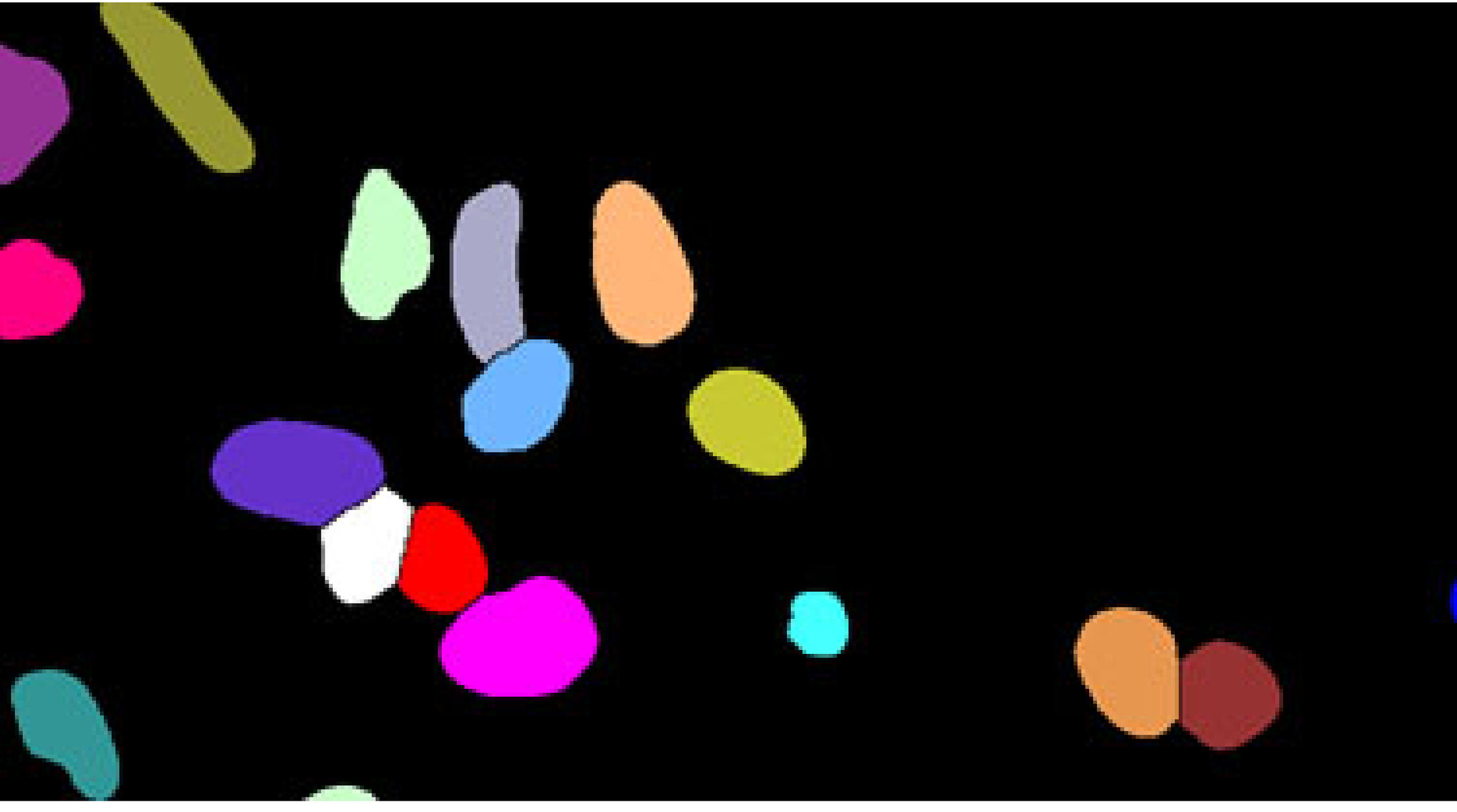


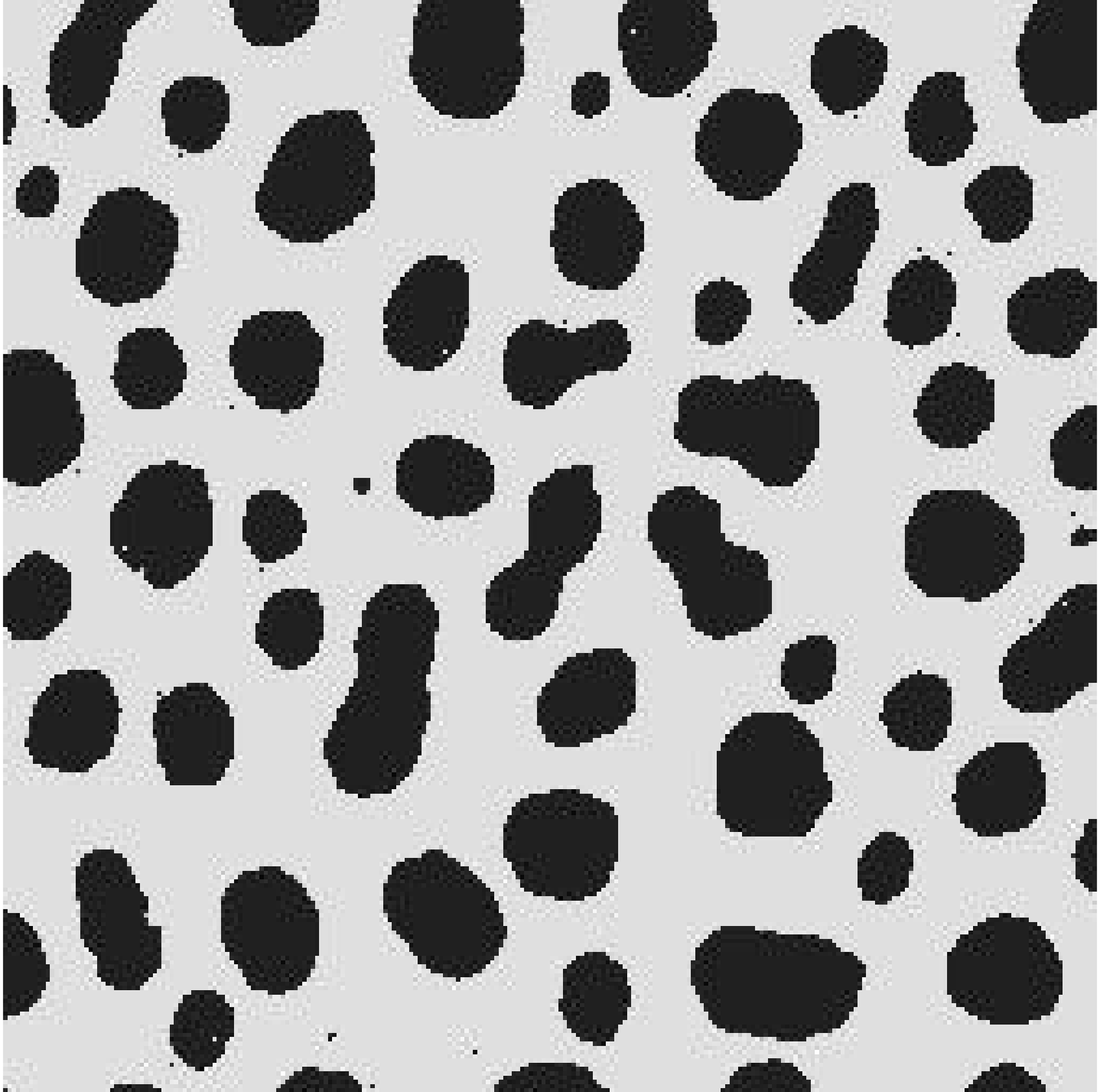


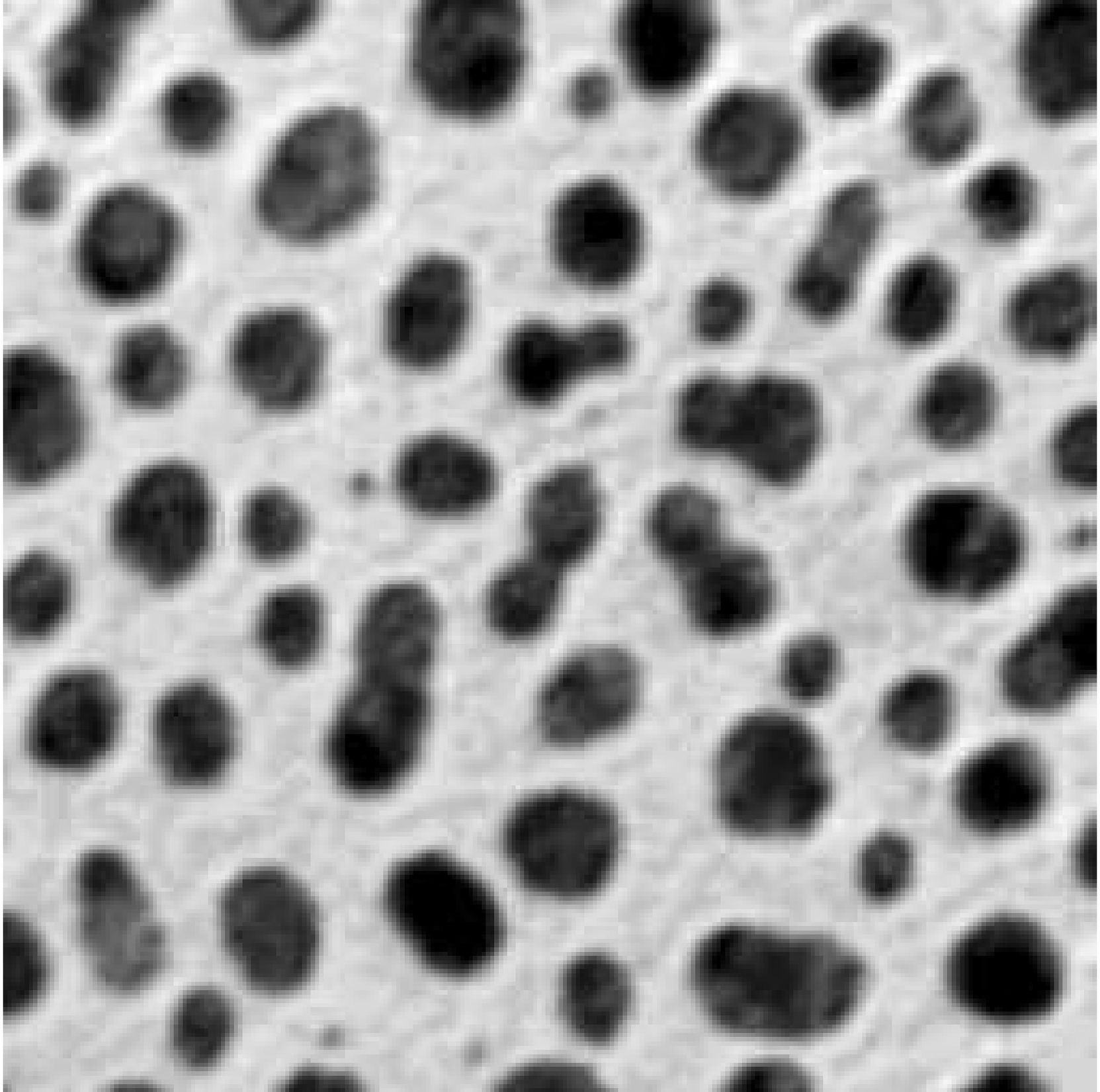


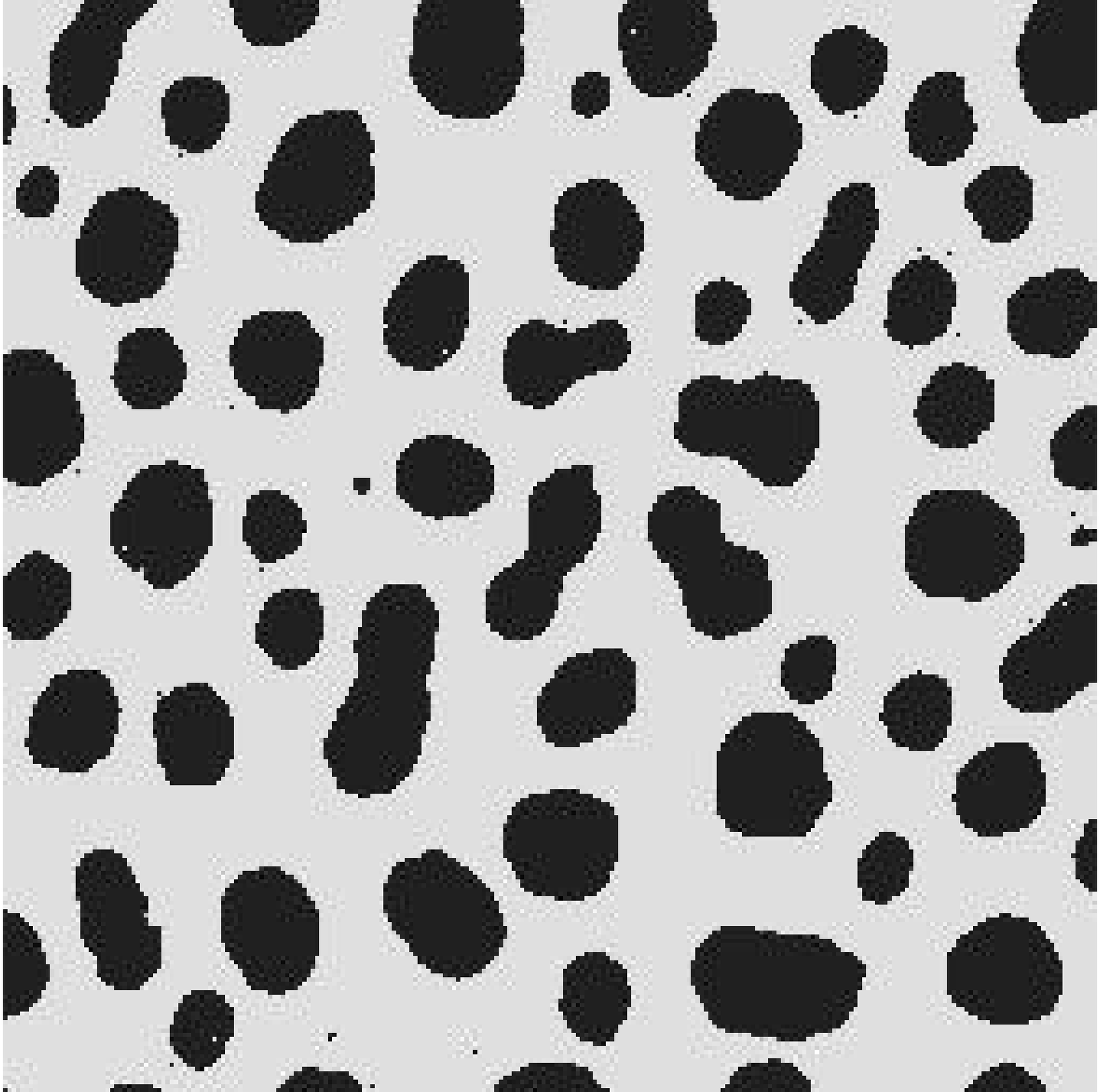


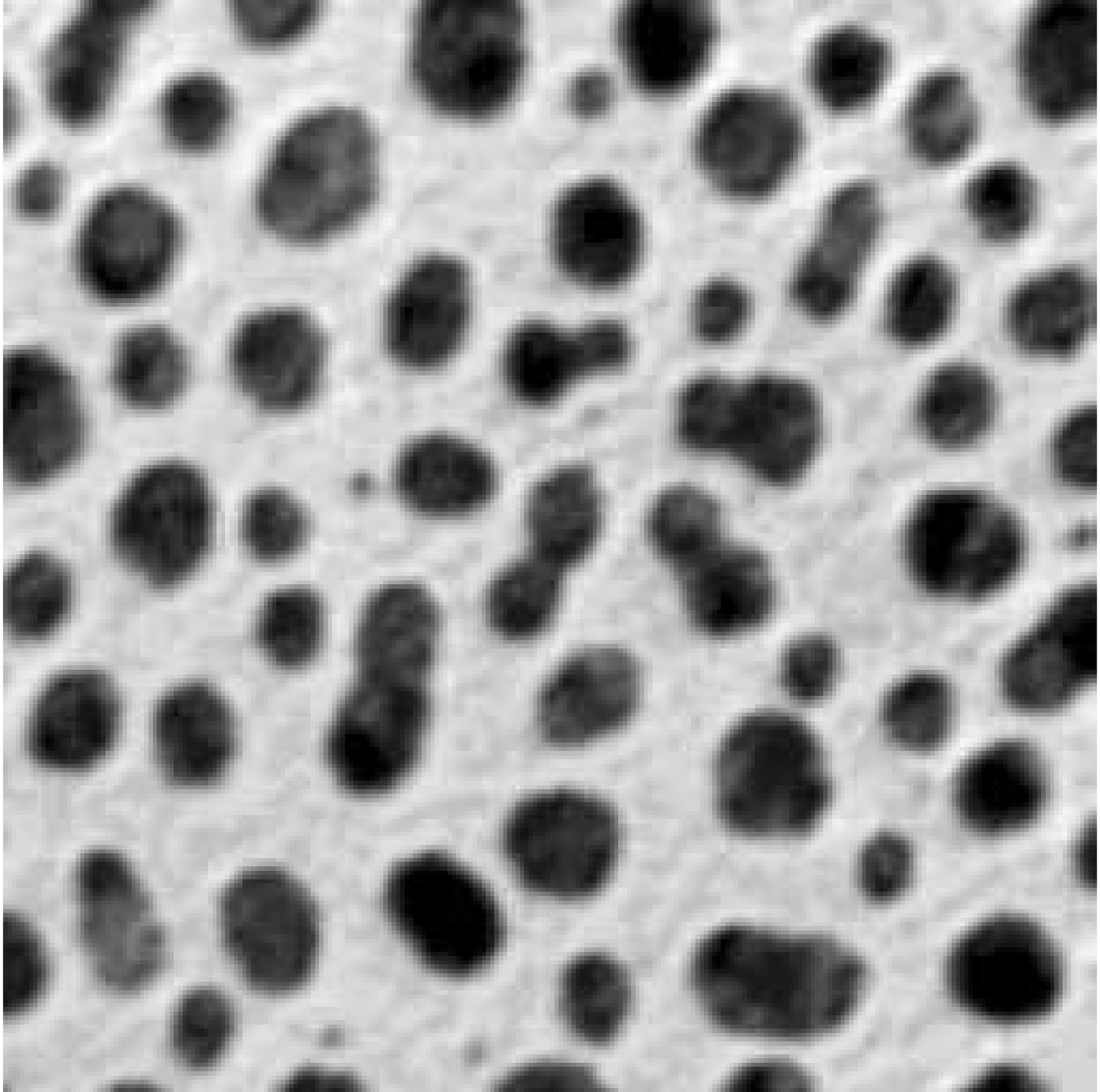


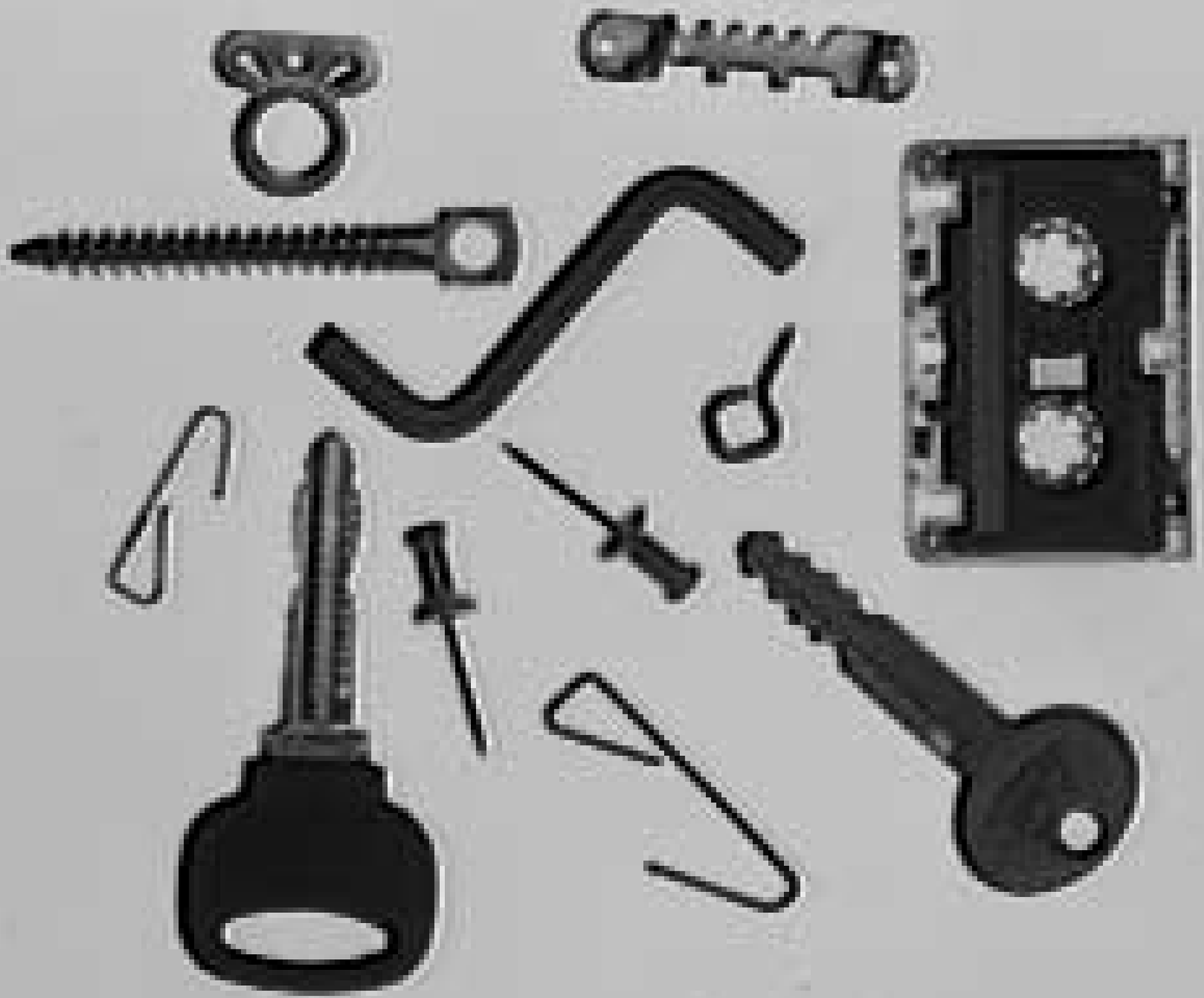


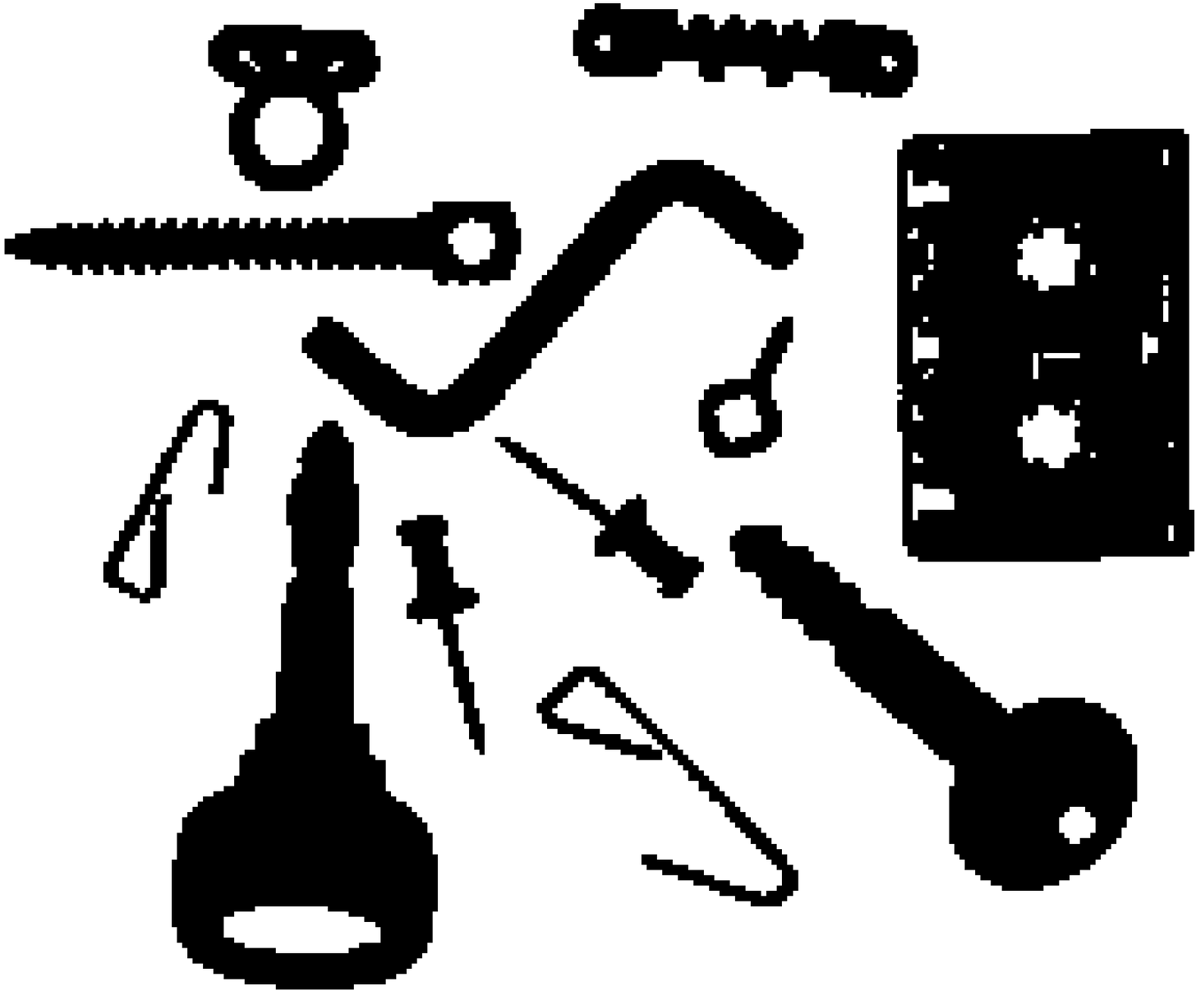


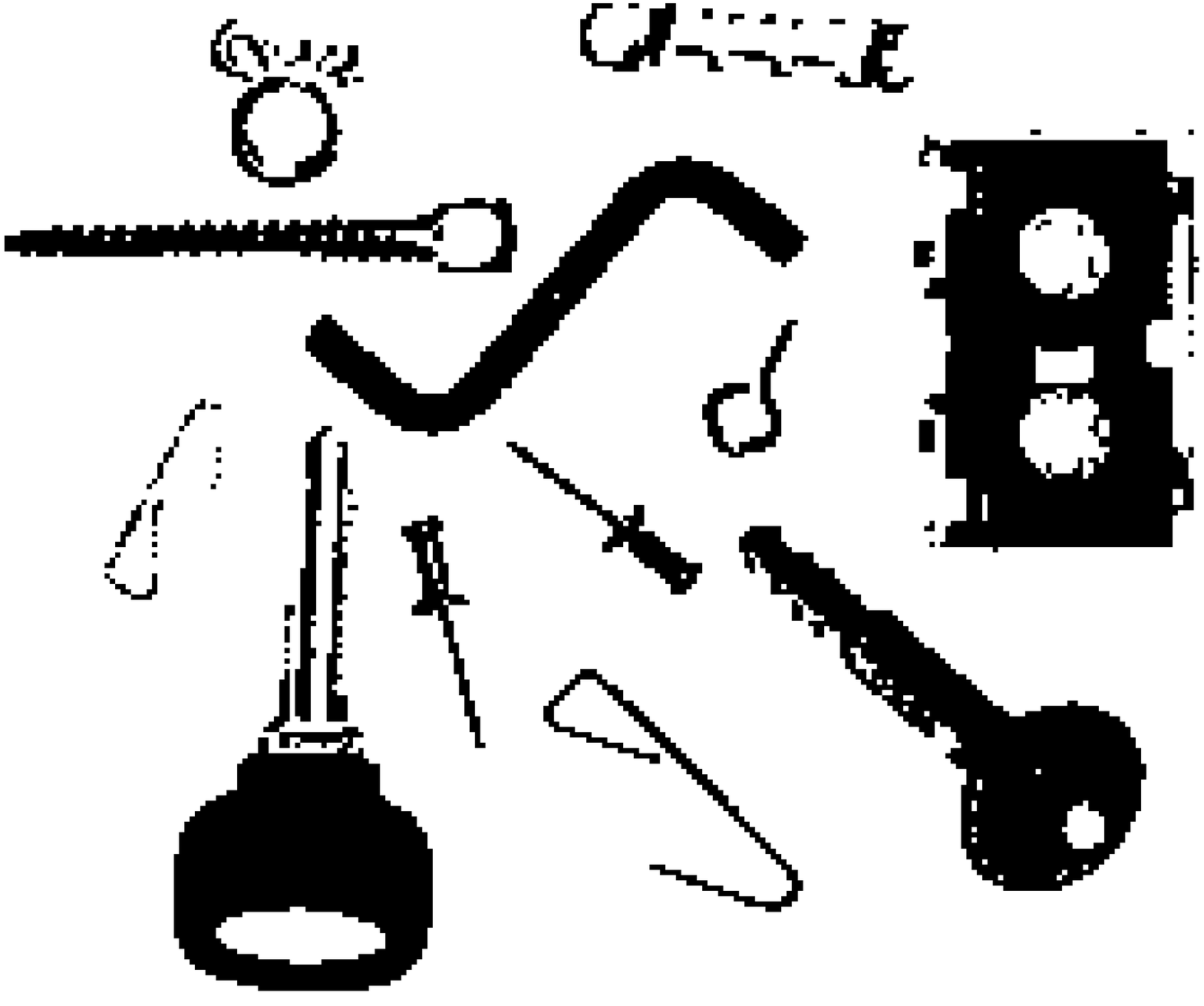


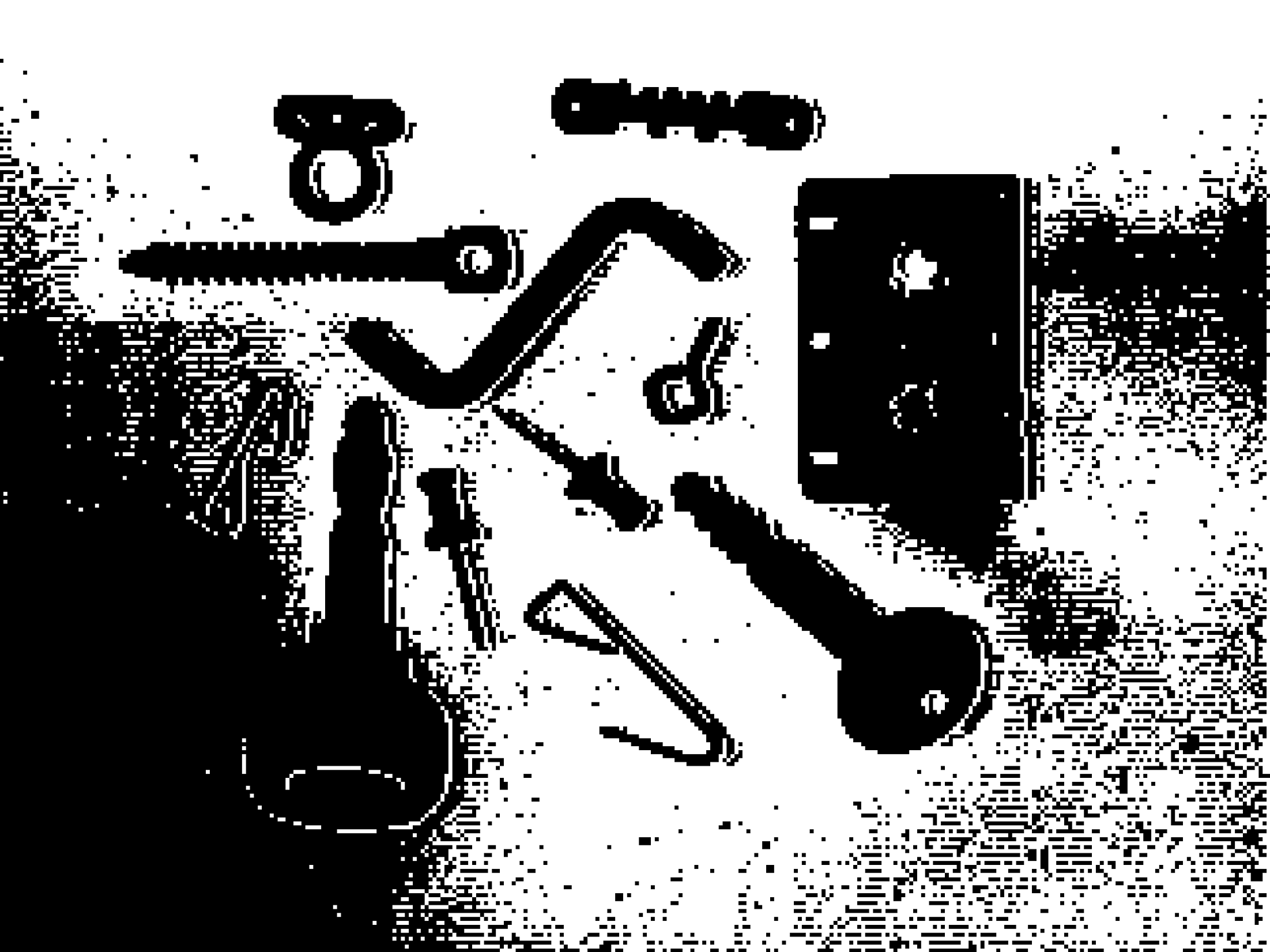


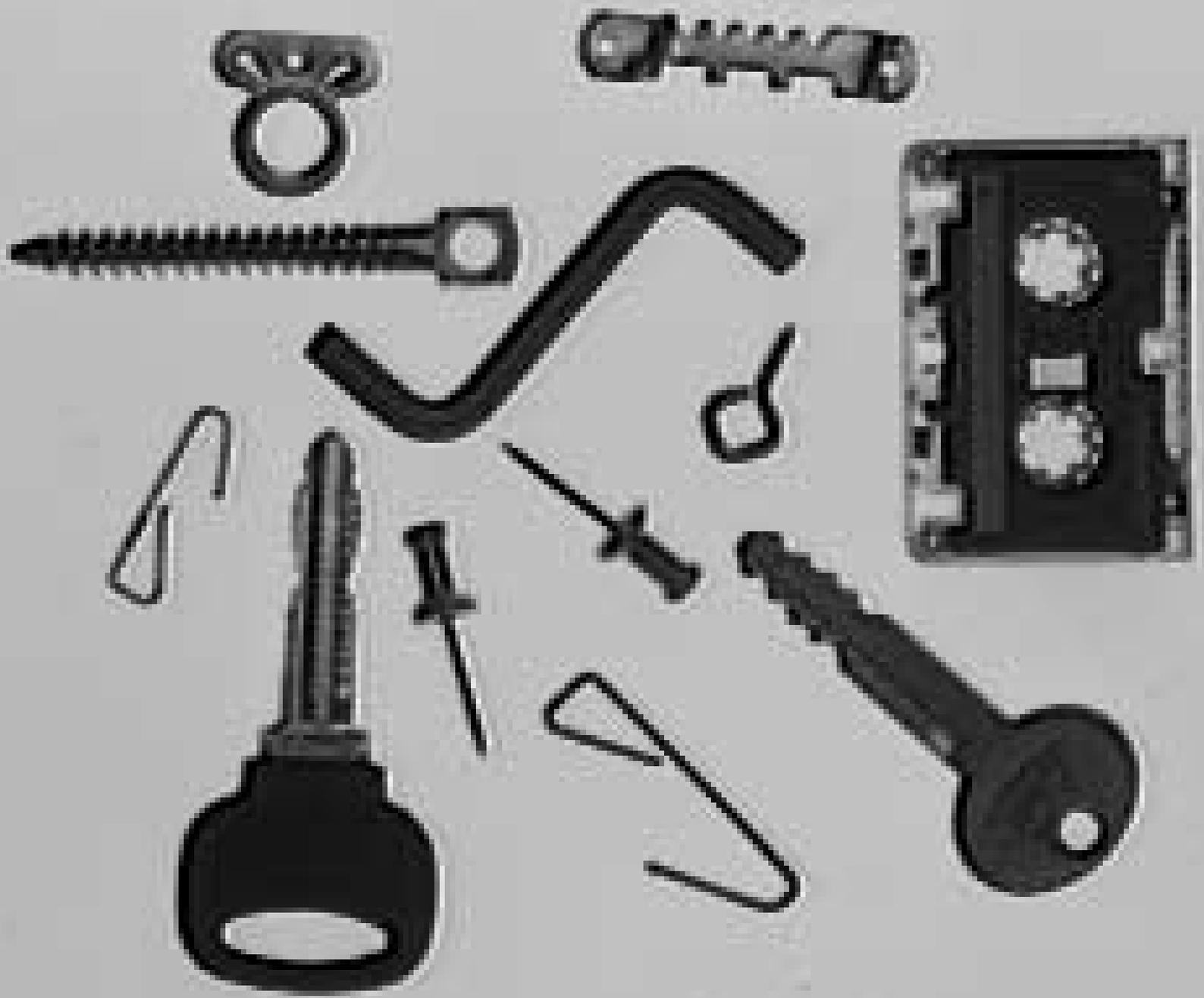


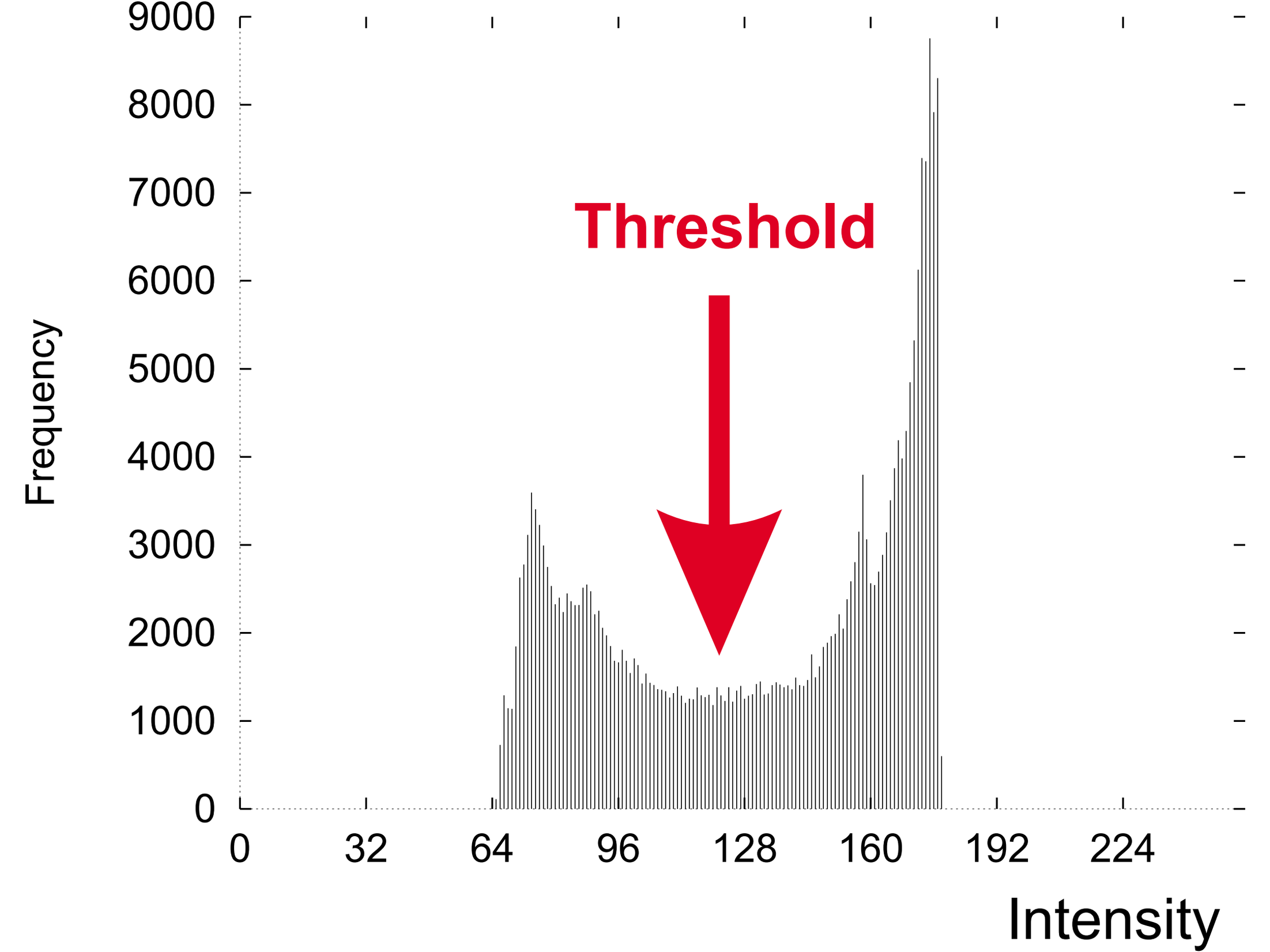


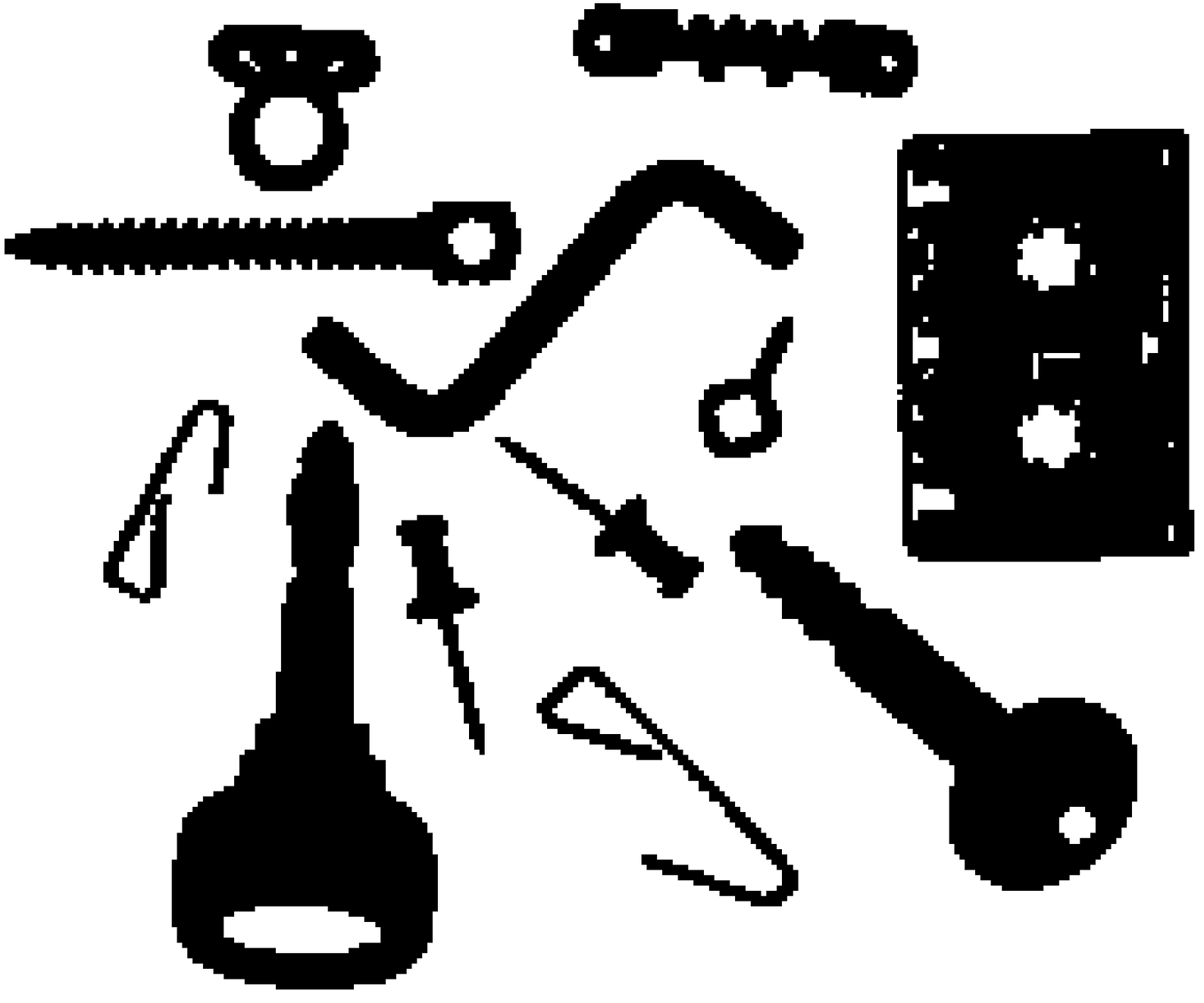


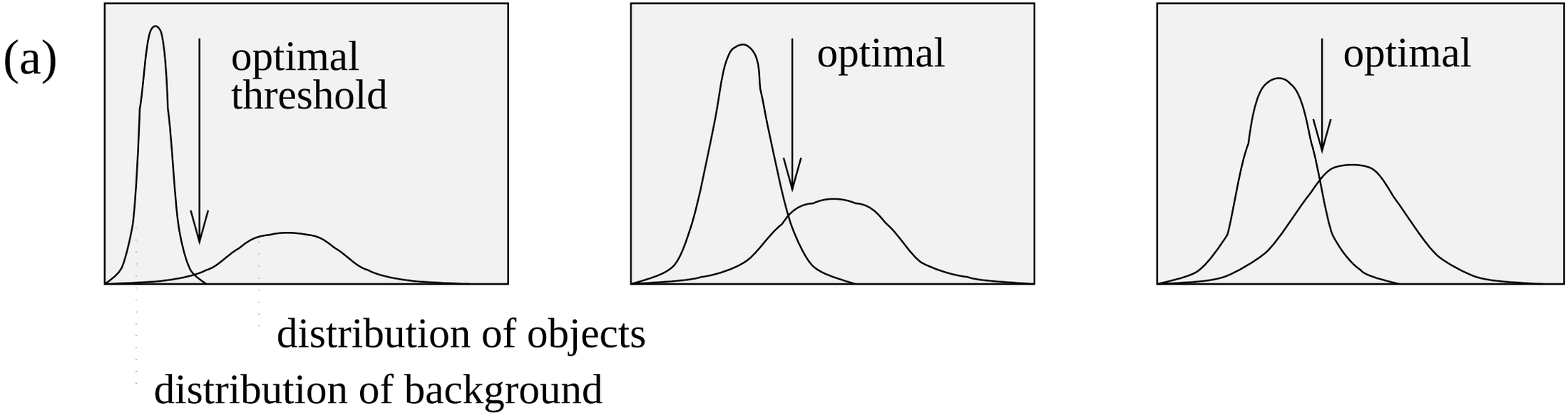


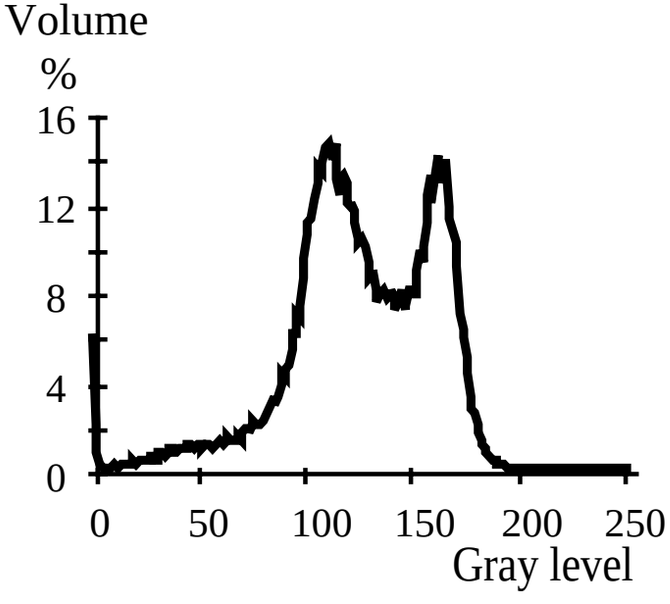




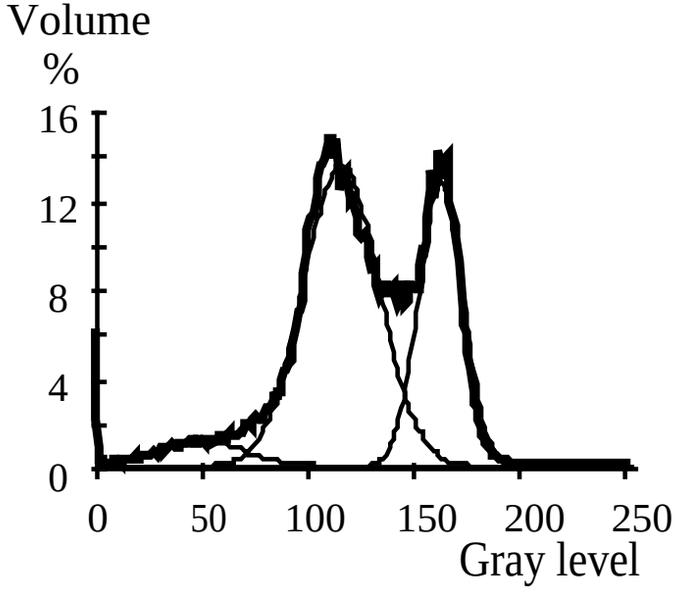

Threshold
Frequency
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
0
32
64
96
128
160
192
224
Intensity



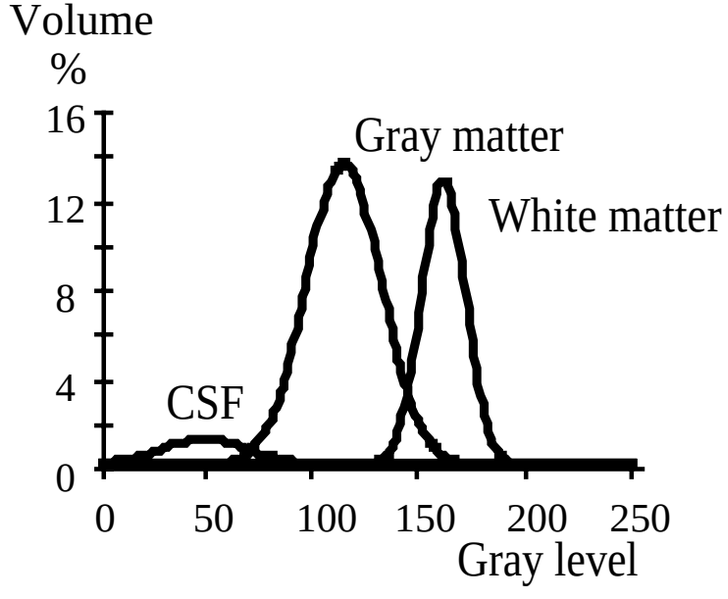

(a)
optimal
threshold
optimal
optimal
distribution of objects
distribution of background
(b)
optimal
threshold
conventional
threshold
optimal
conventional
conventional
???
optimal


Volume
%
16
12
8
4
0
0
50
100
150
200
250
Gray level

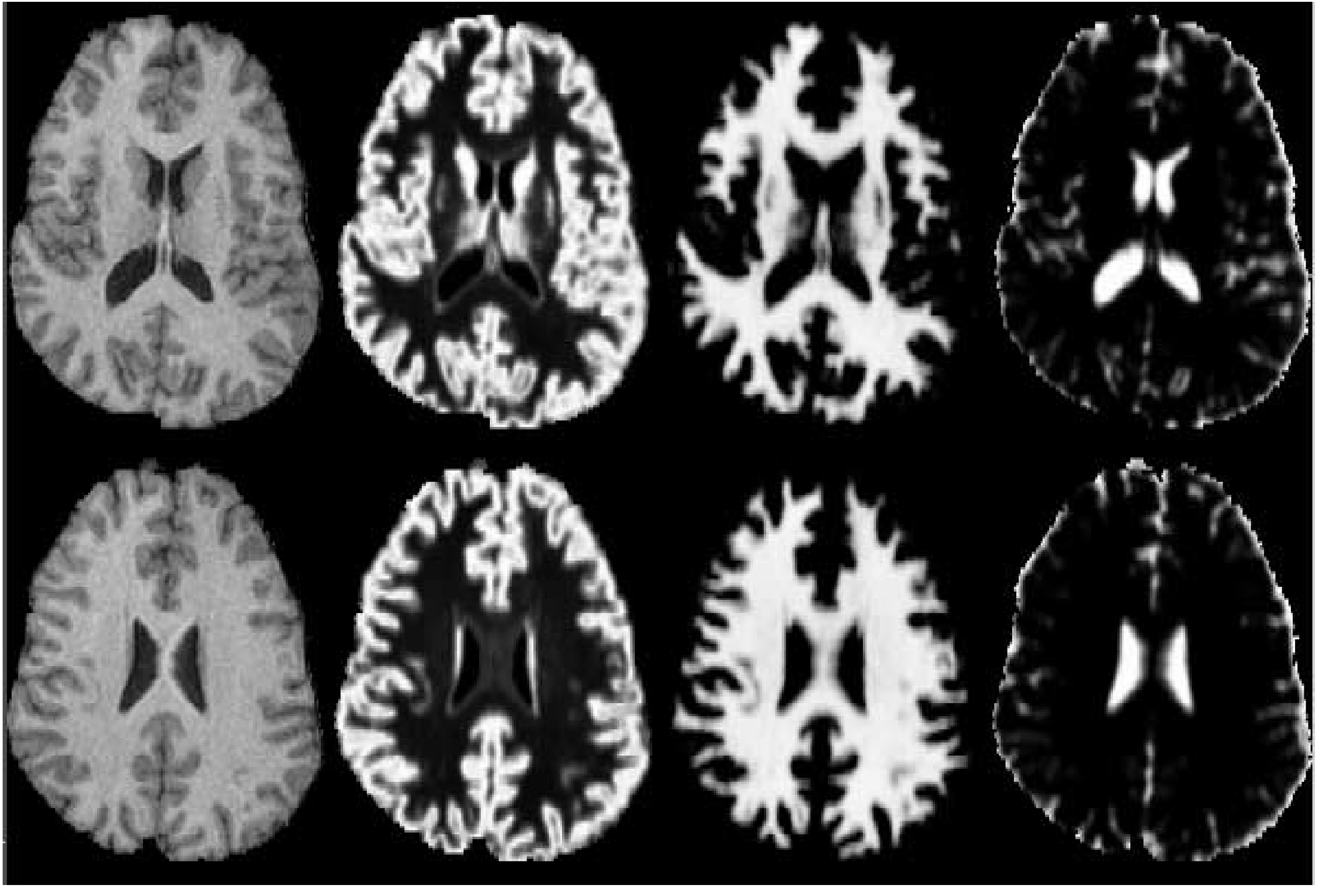
(a)

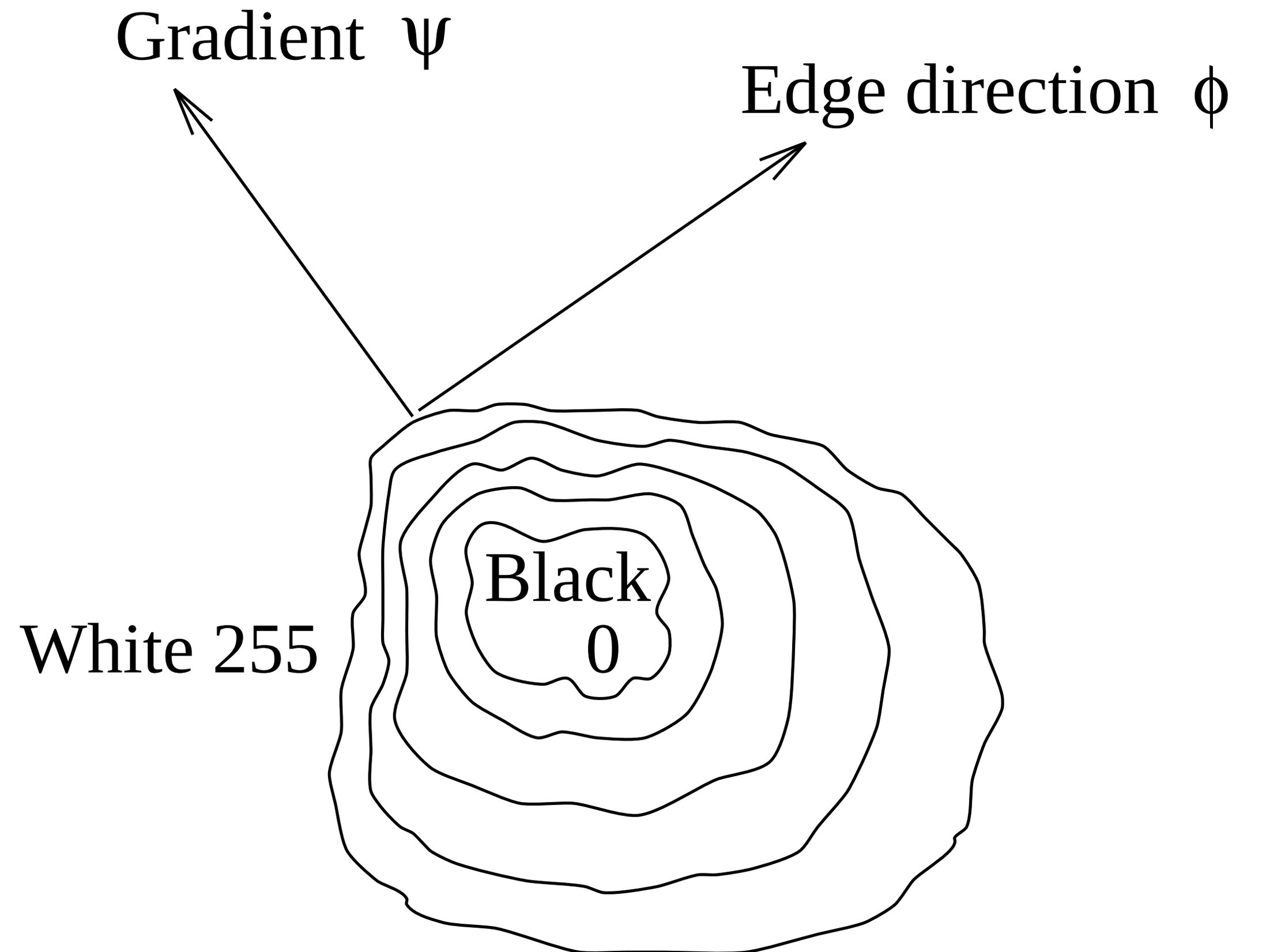

Volume
%
16
12
8
4
0
0
50
100
150
200
250
Gray level

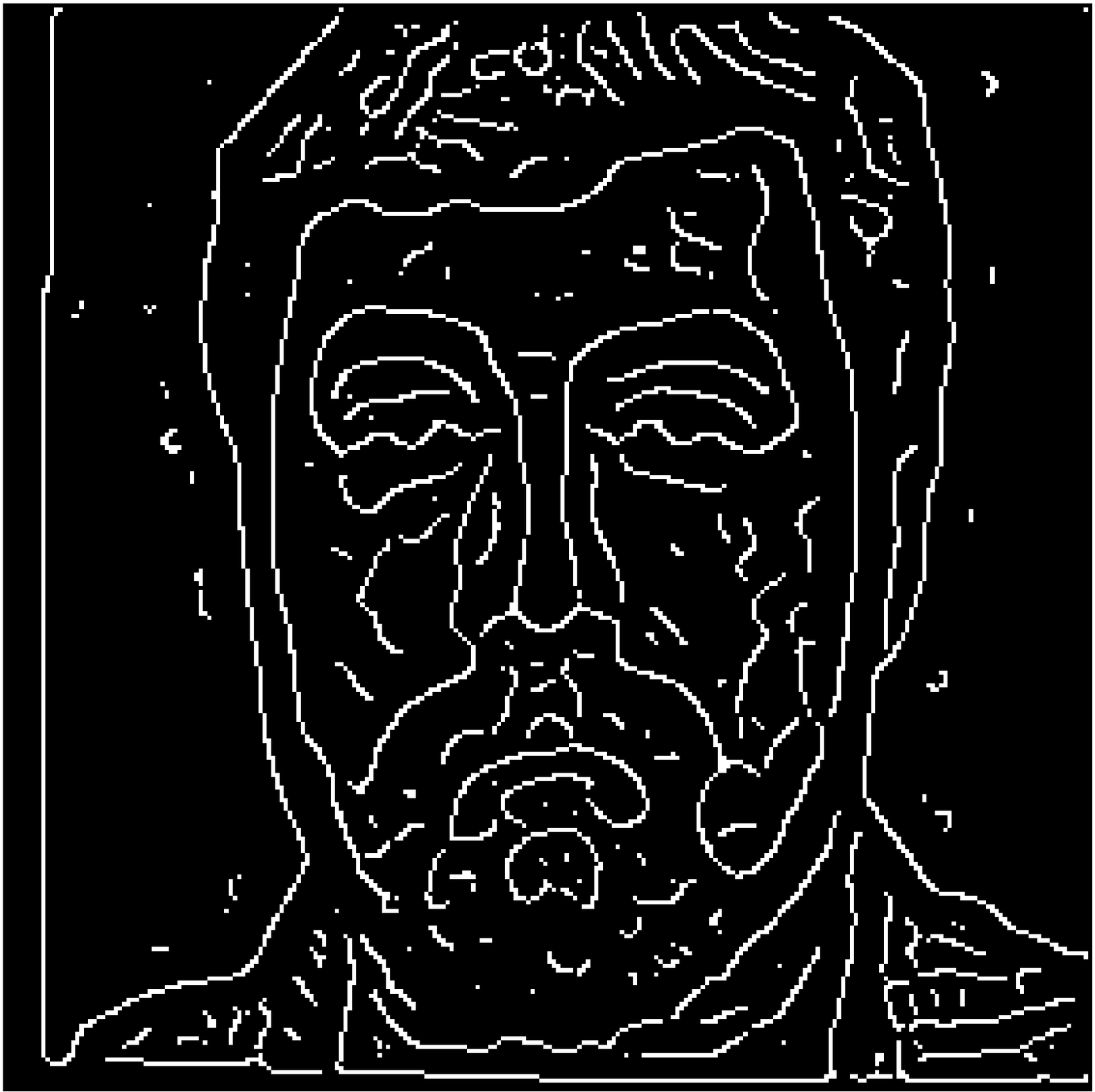
(b)

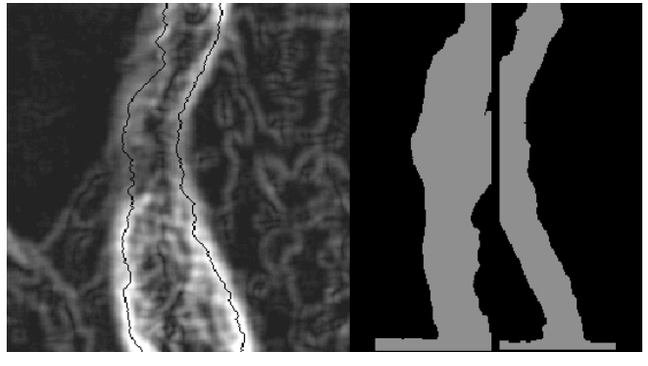

Volume
%
16
12
8
4
0
Gray matter
White matter
CSF
0
50
100
150
200
250
Gray level

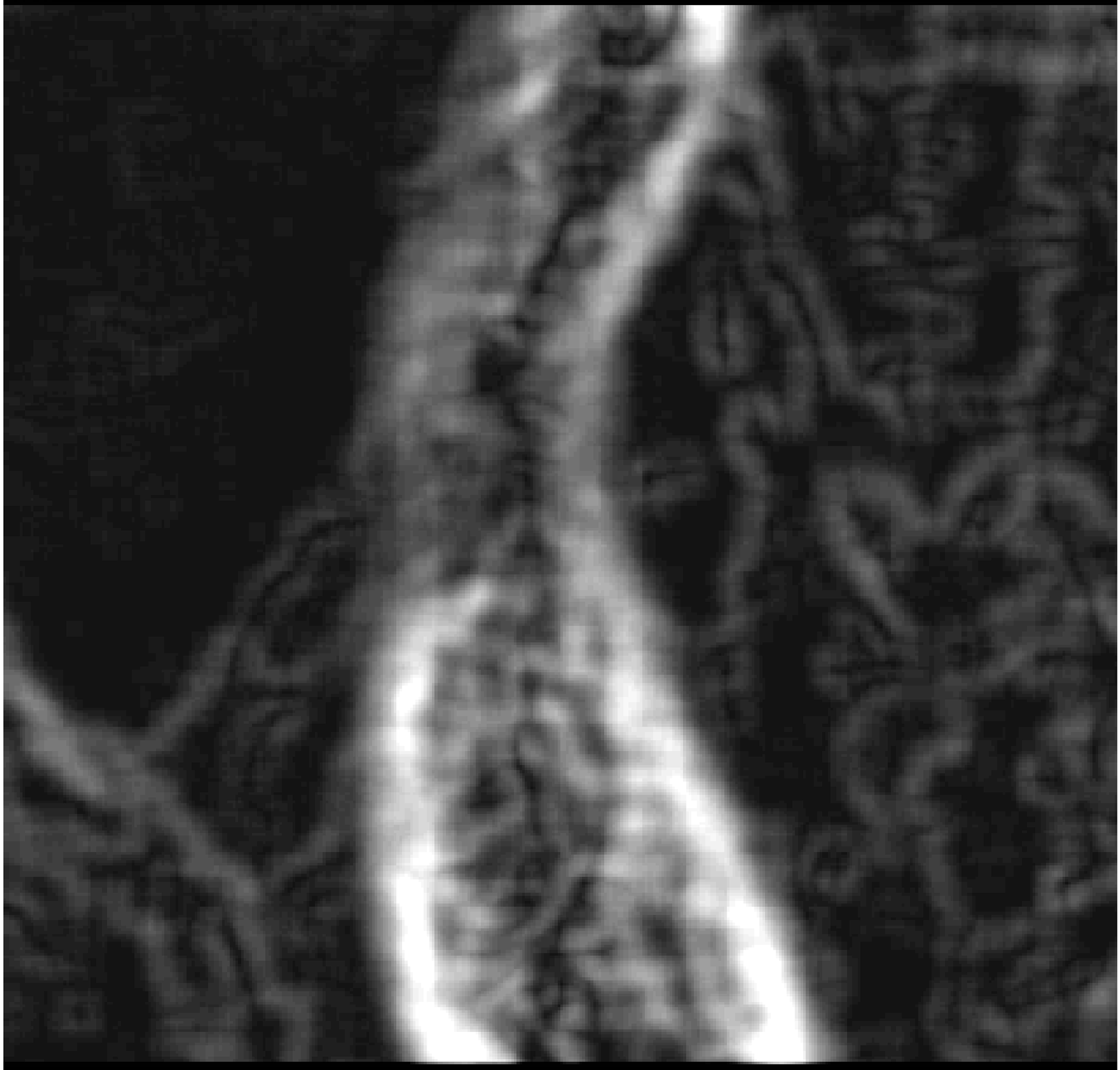
(c)

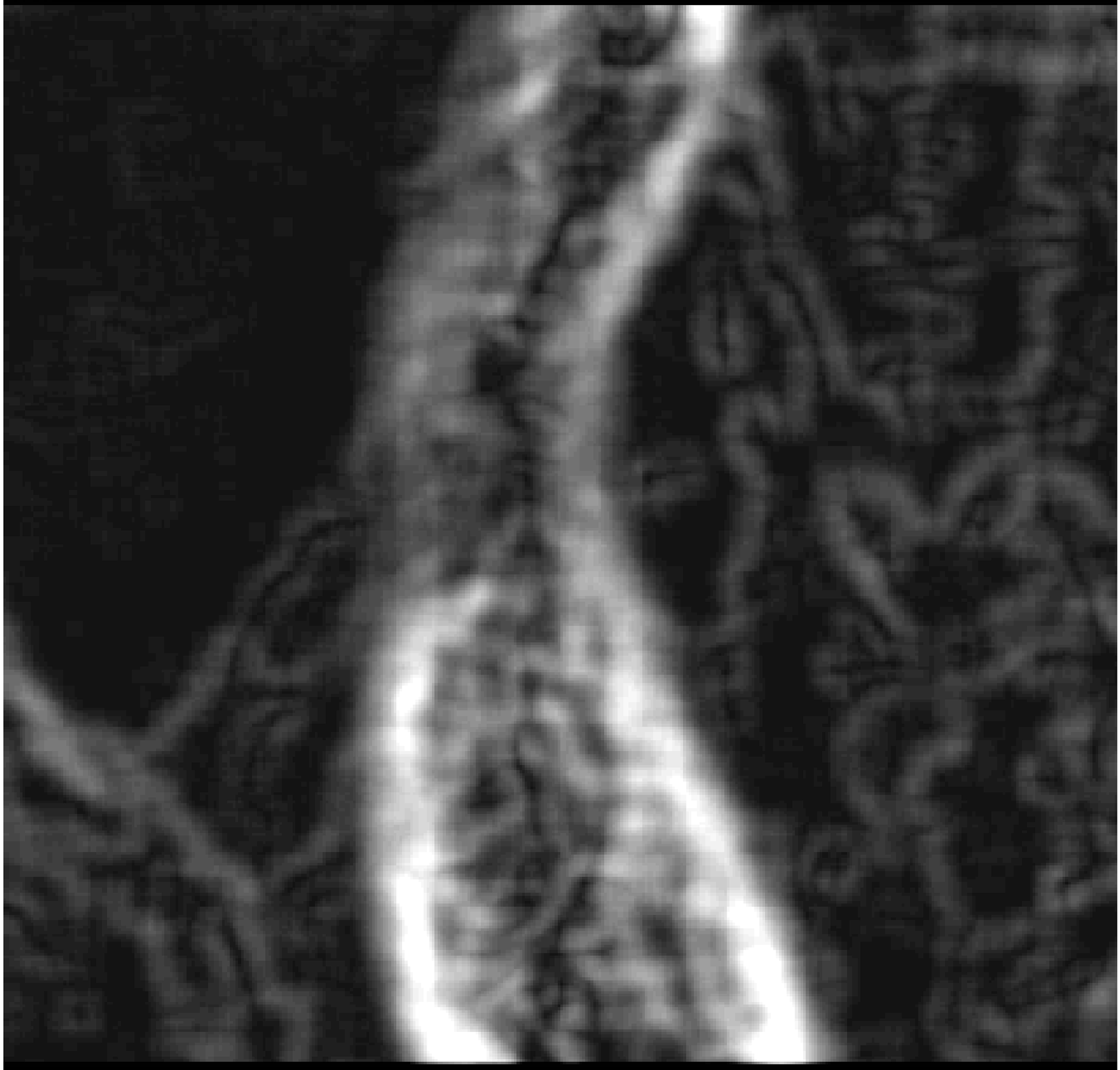


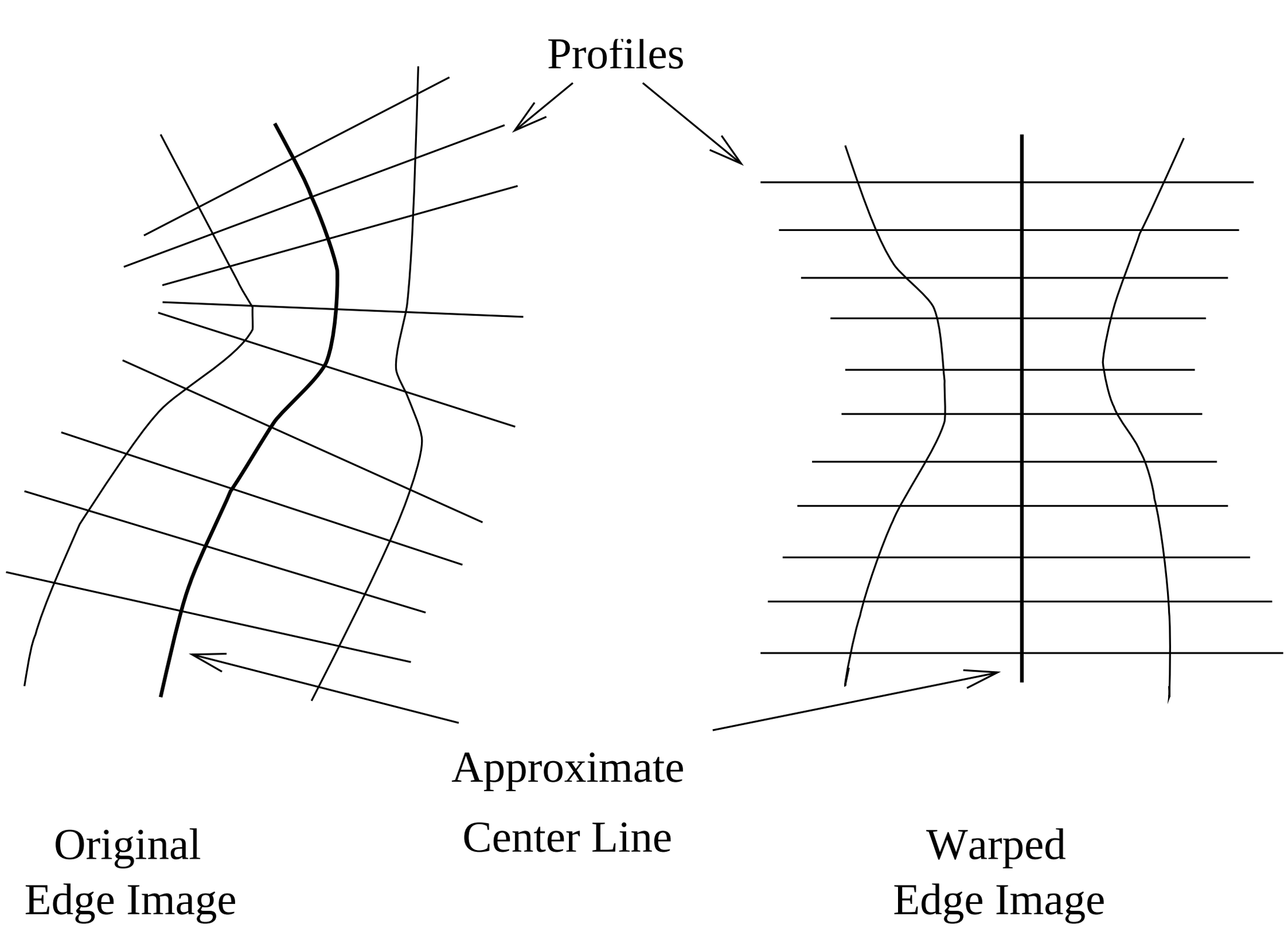

Gradient ψ
Edge direction ϕ
White 255
Black
0

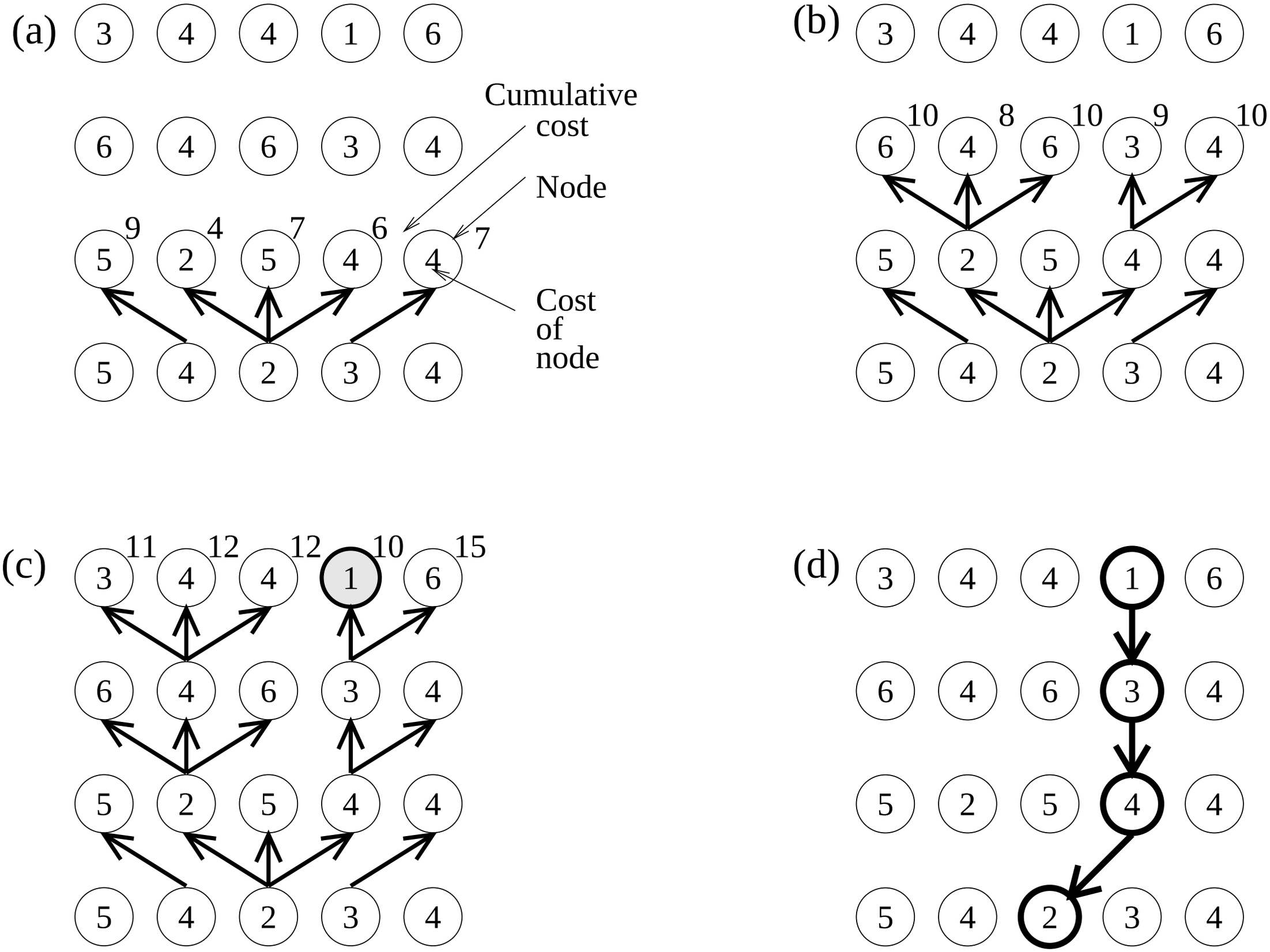


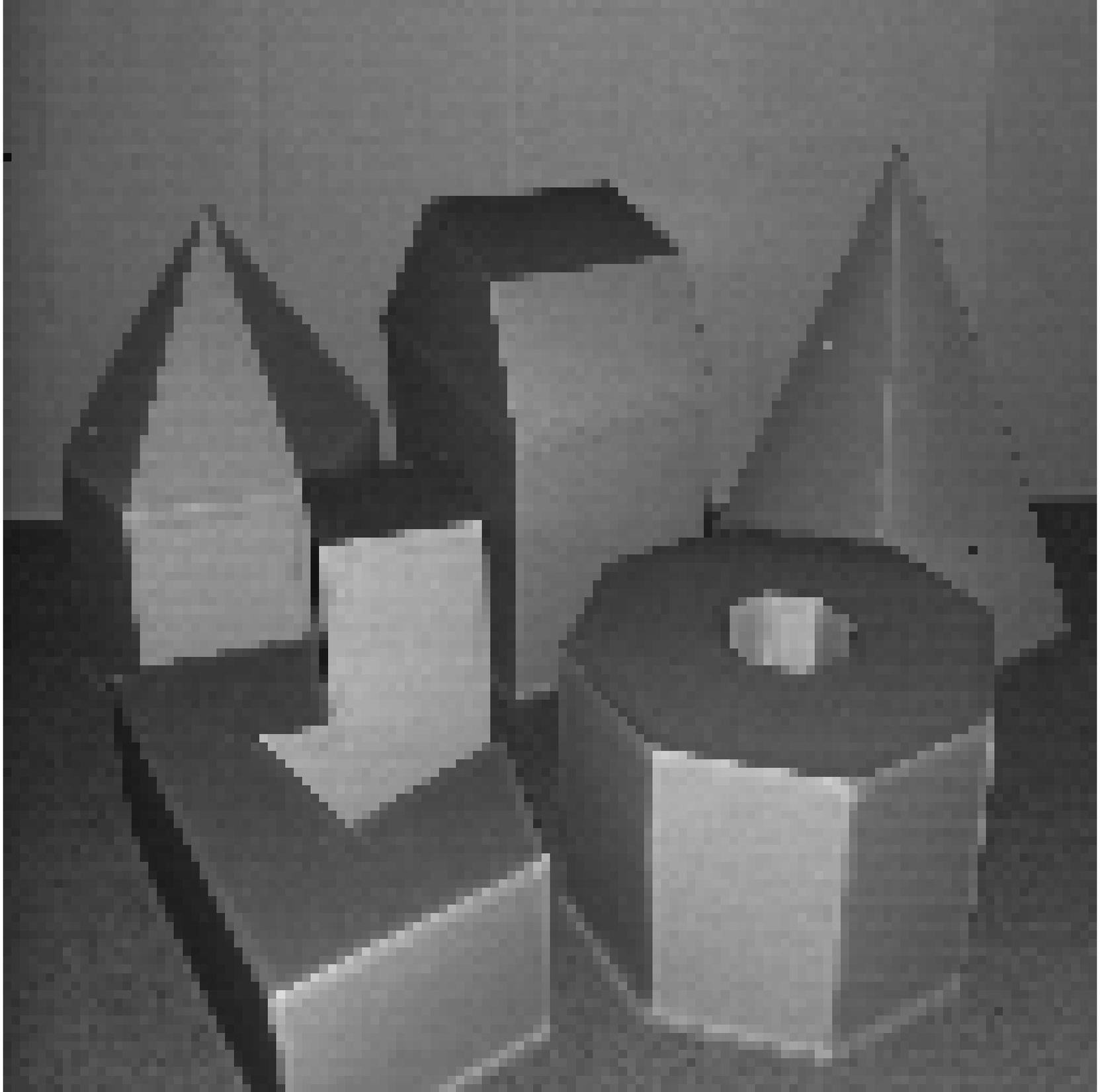


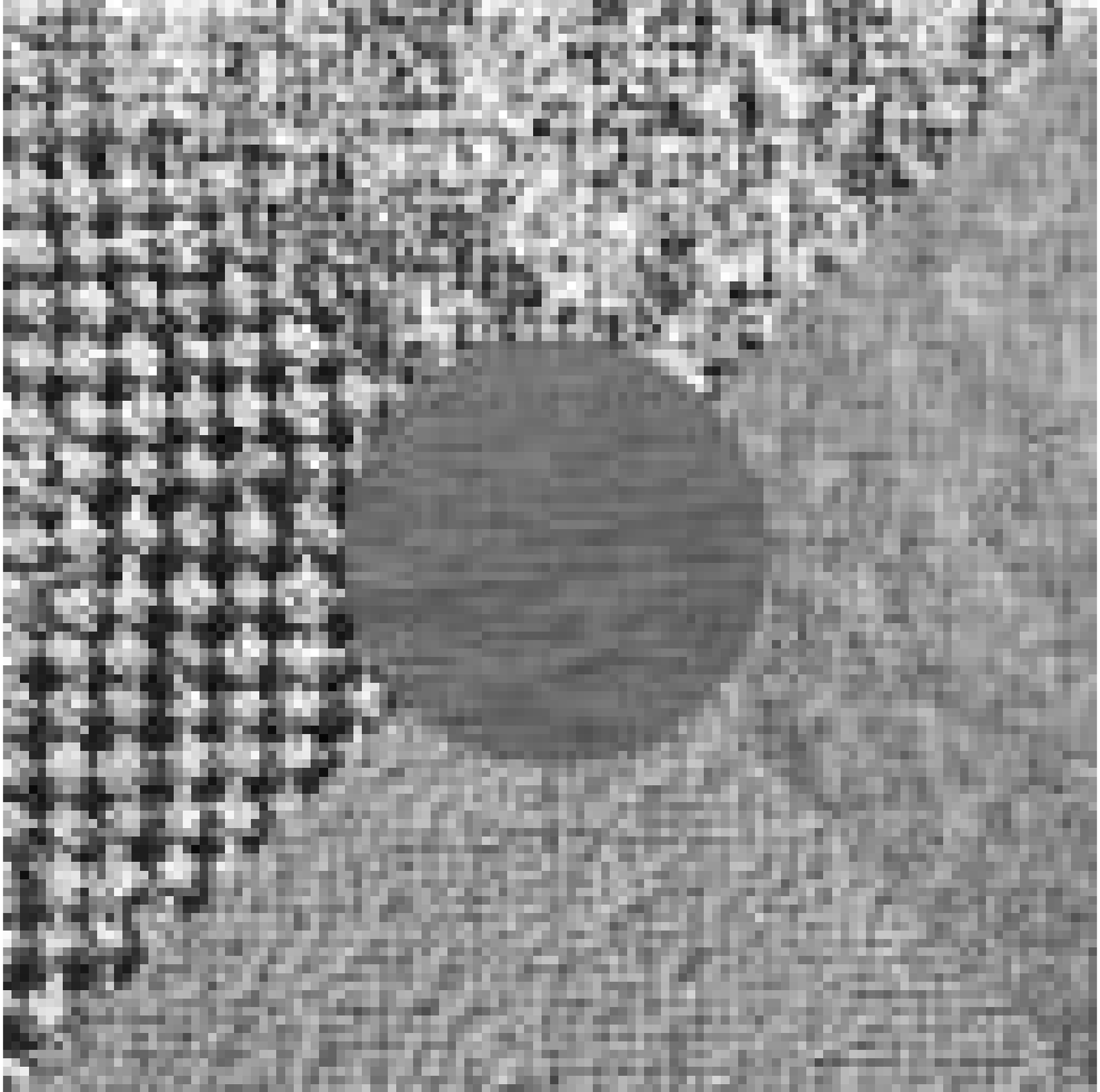


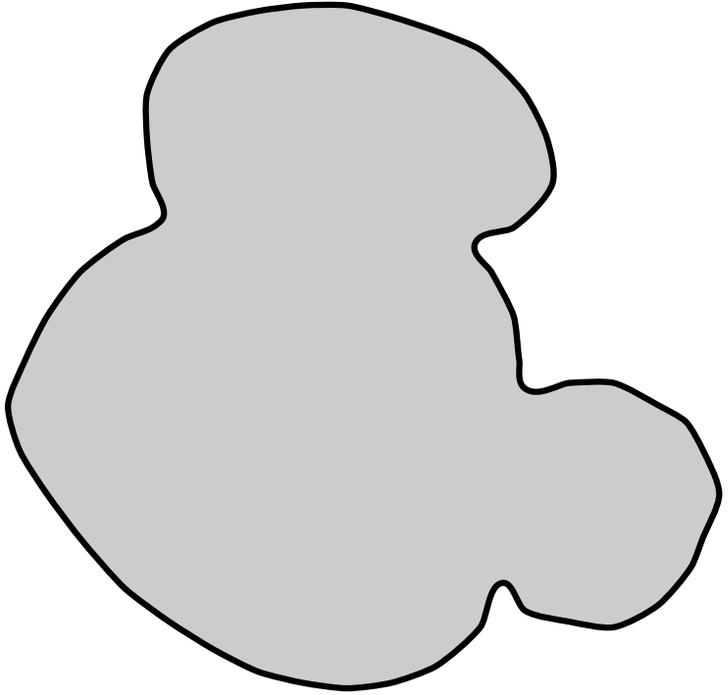



Profiles
Approximate
Center Line
Original
Edge Image
Warped
Edge Image

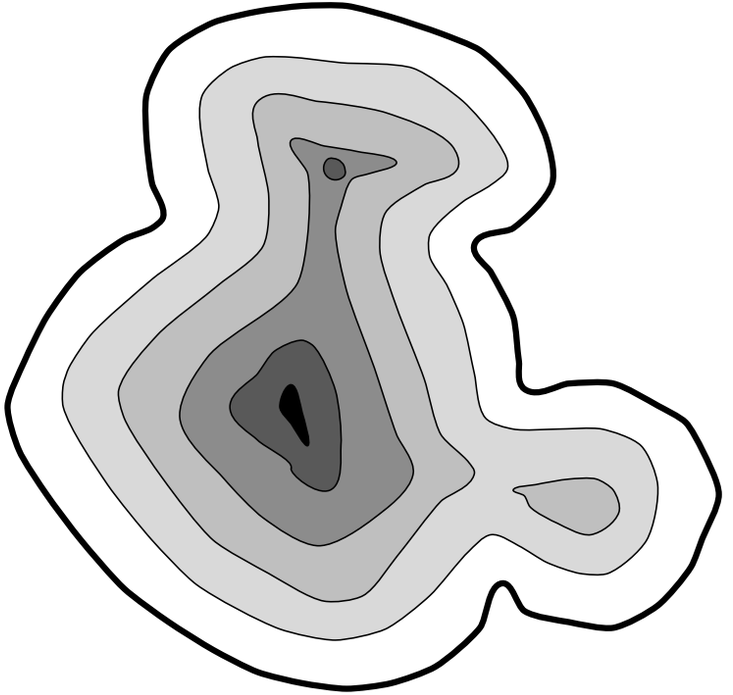

(a)
3 4 4 1 6
Cumulative cost
Node
6 4 6 3 4
9 4 7 6 7
5 2 5 4 4
Cost of node
5 4 2 3 4
(b)
3 4 4 1 6
10 8 10 9 10
6 4 6 3 4
5 2 5 4 4
5 4 2 3 4
(c)
11 12 12 10 15
3 4 4 1 6
6 4 6 3 4
5 2 5 4 4
5 4 2 3 4
(d)
3 4 4 1 6
6 4 6 3 4
5 2 5 4 4
5 4 2 3 4



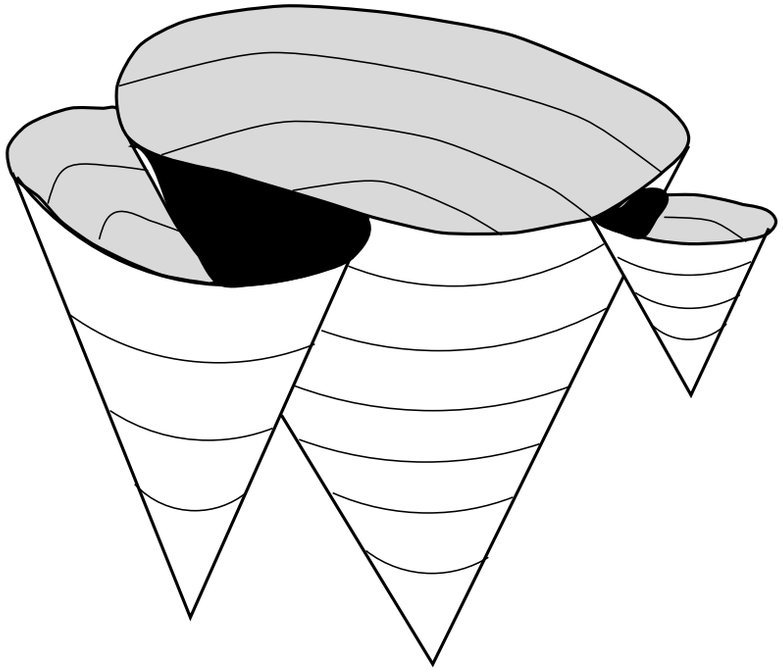




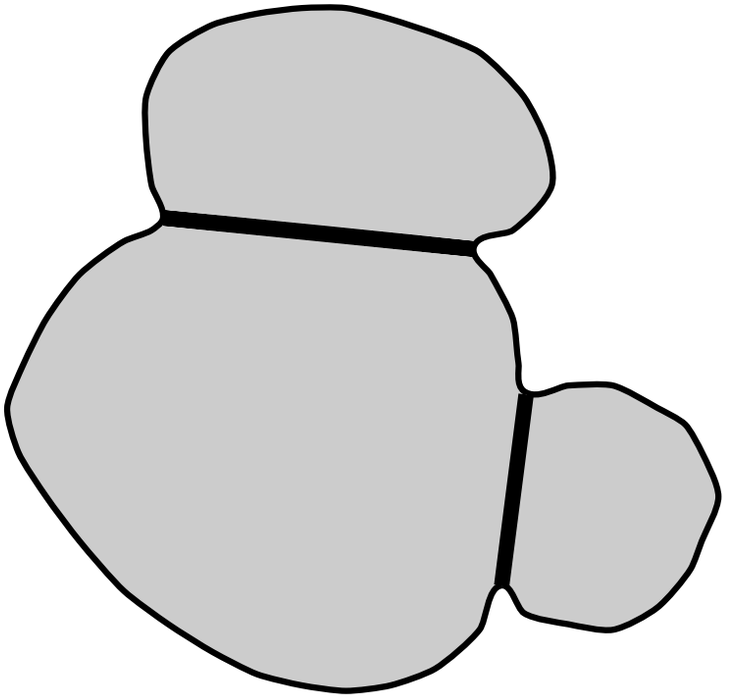
(a)



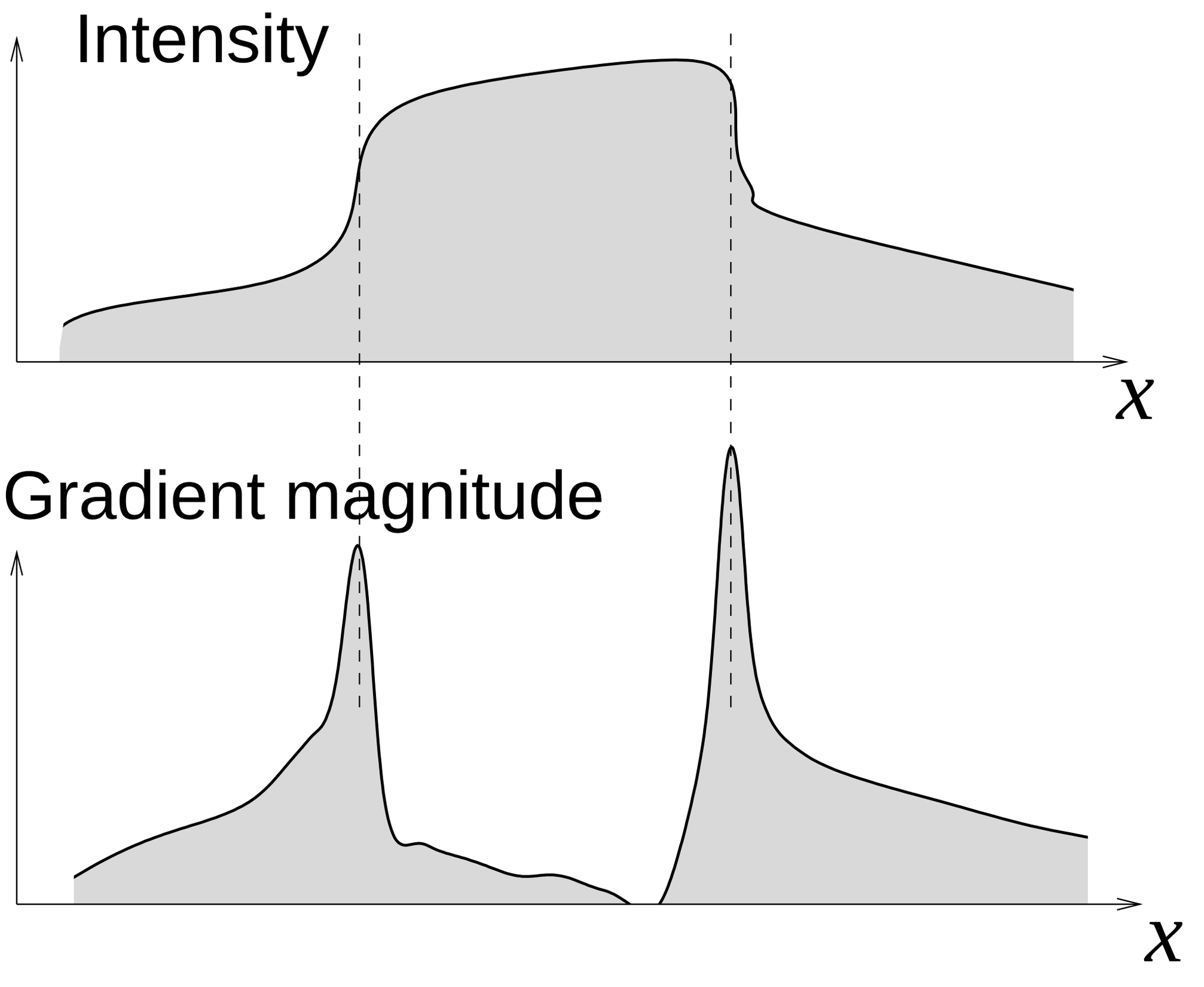
(b)

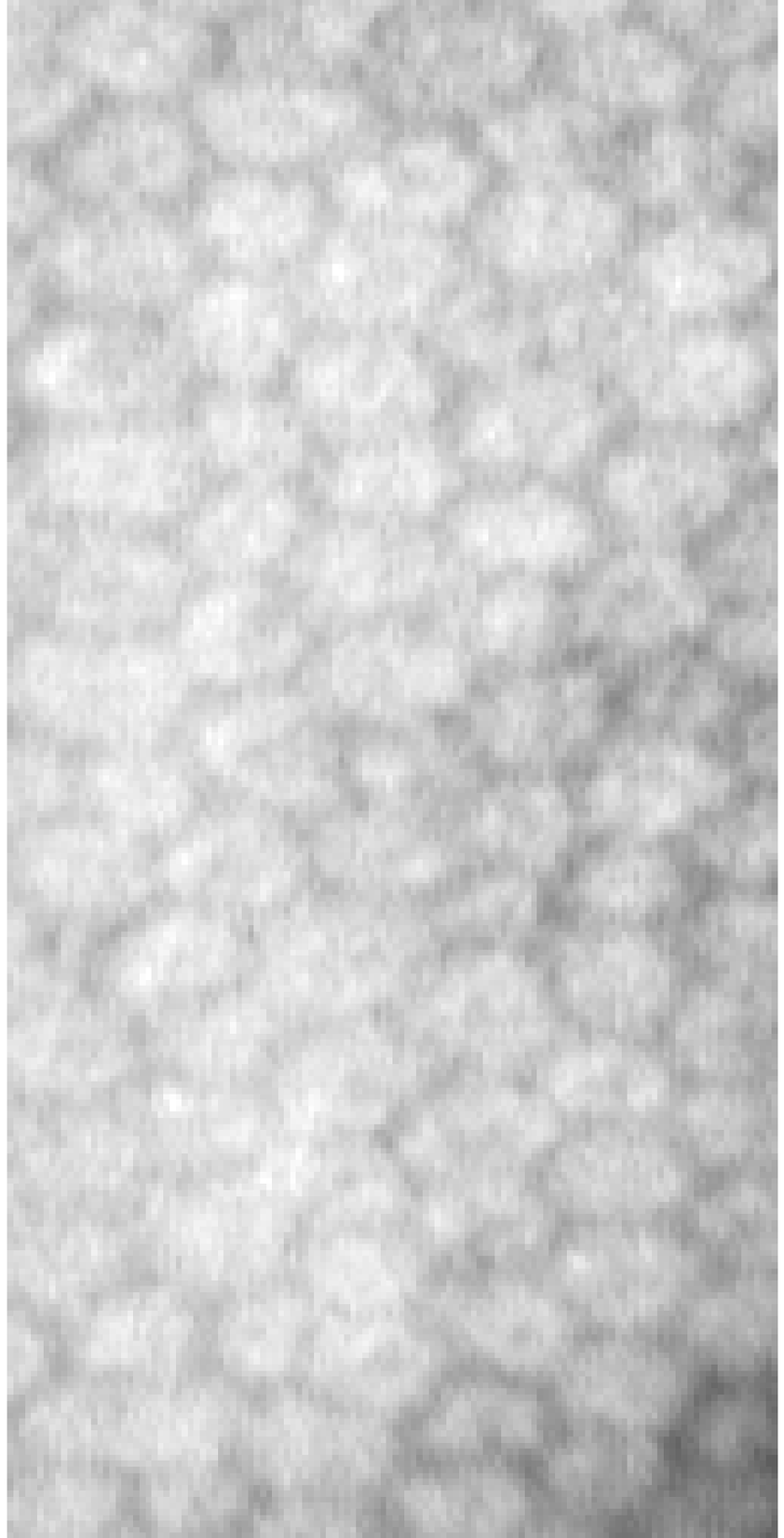


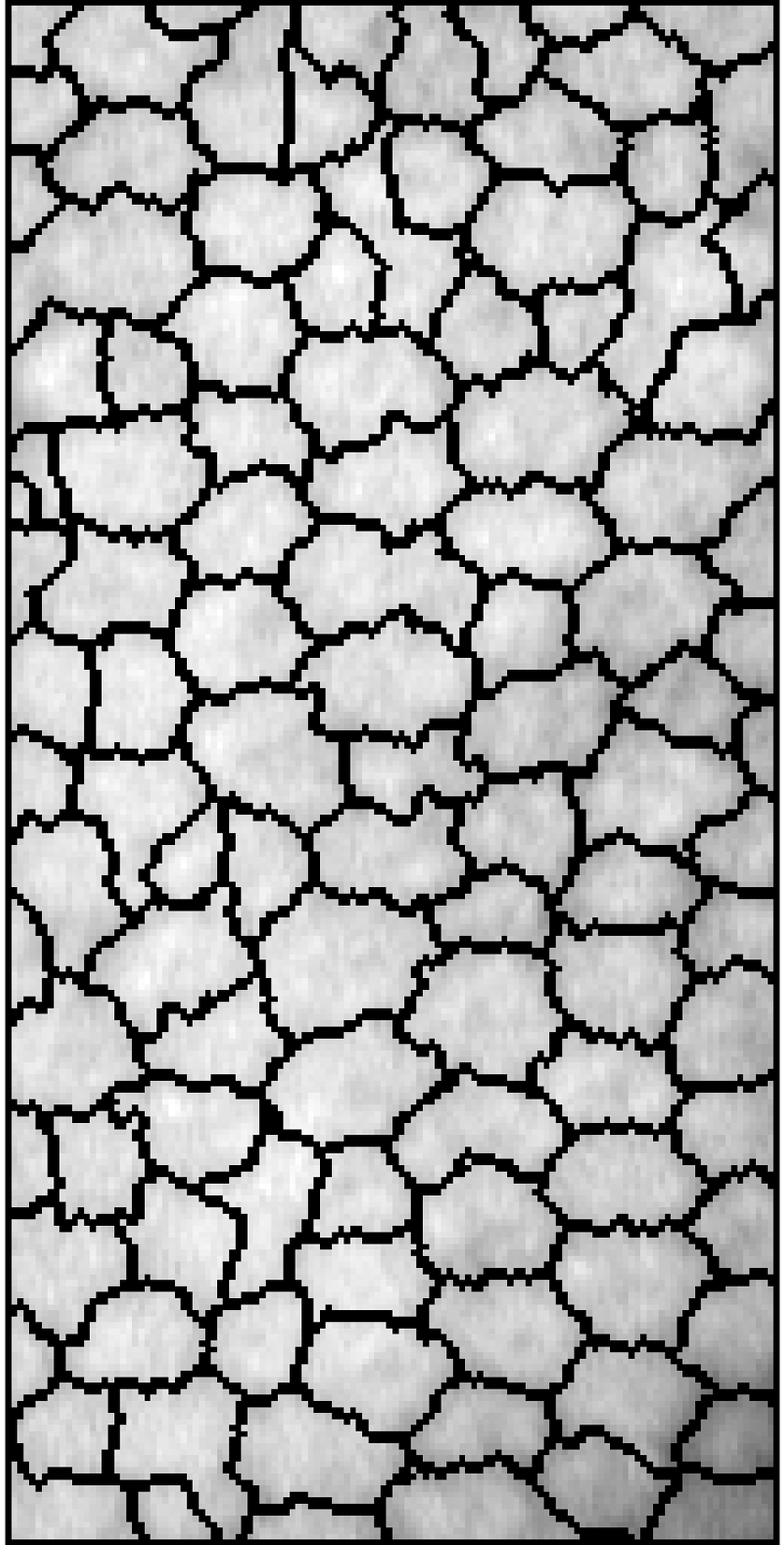
(c)



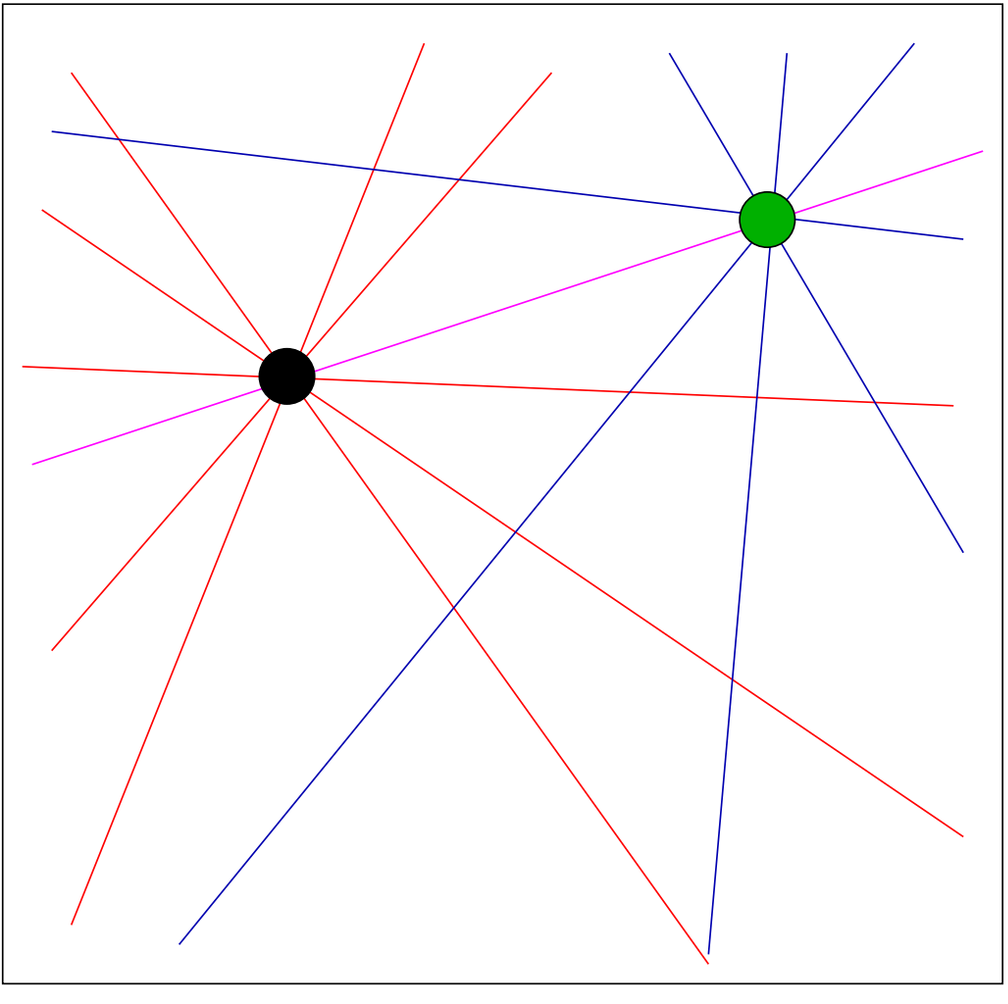
(d)


Intensity
x
Gradient magnitude
x

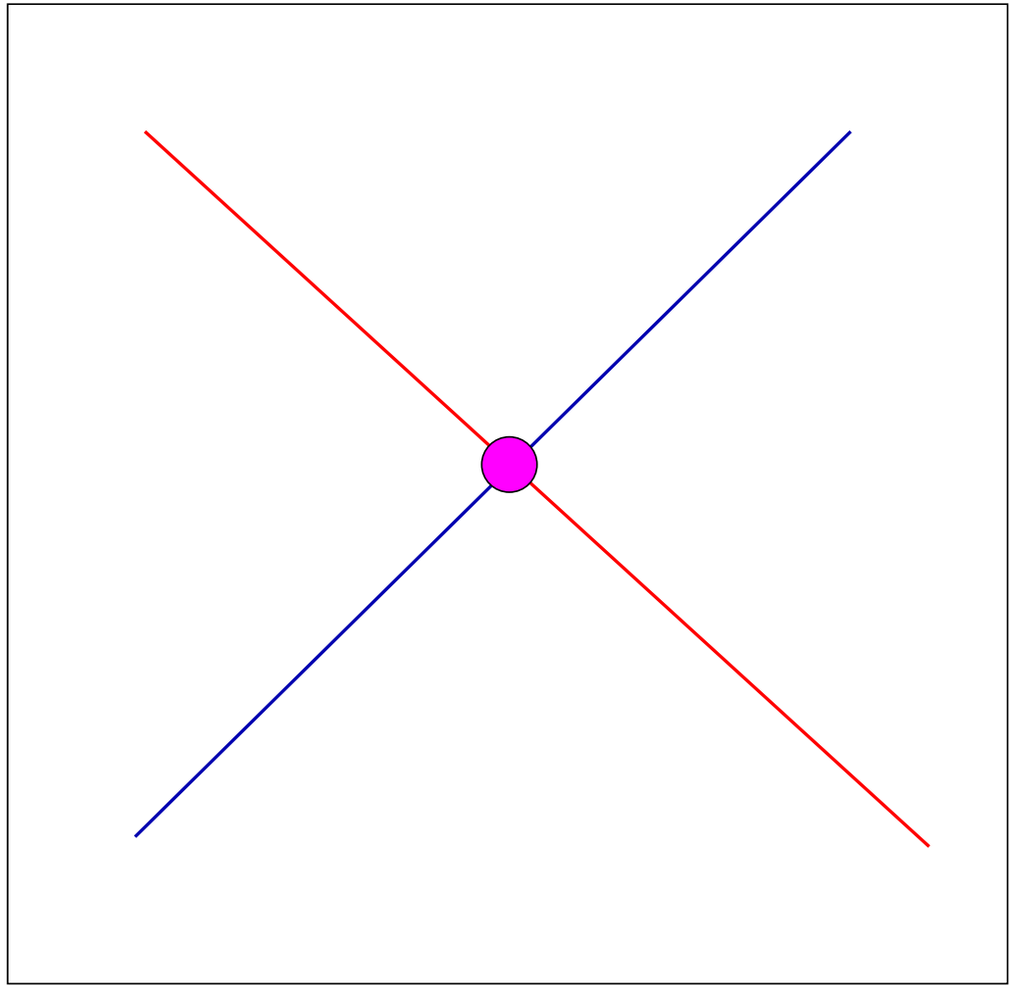


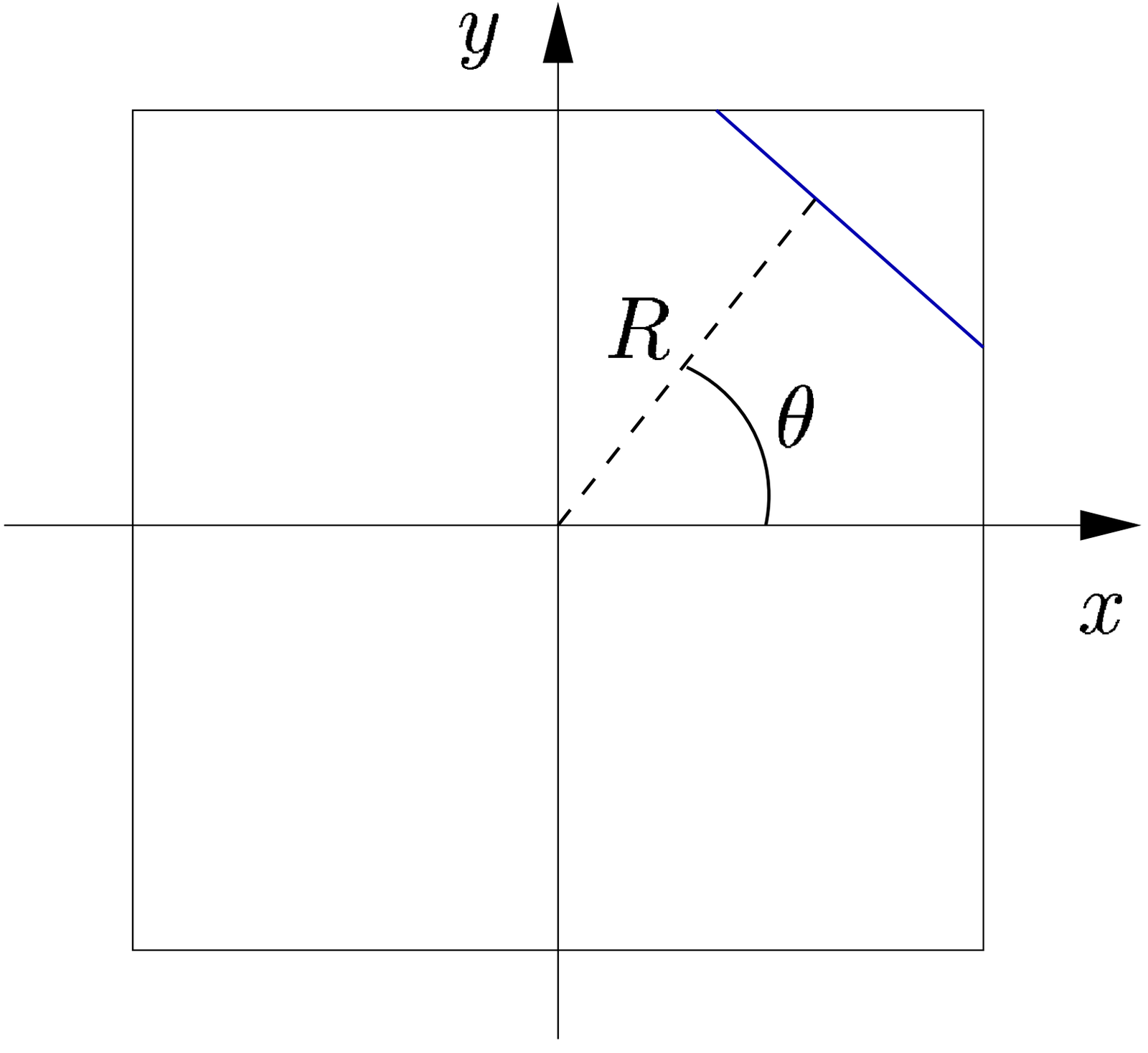


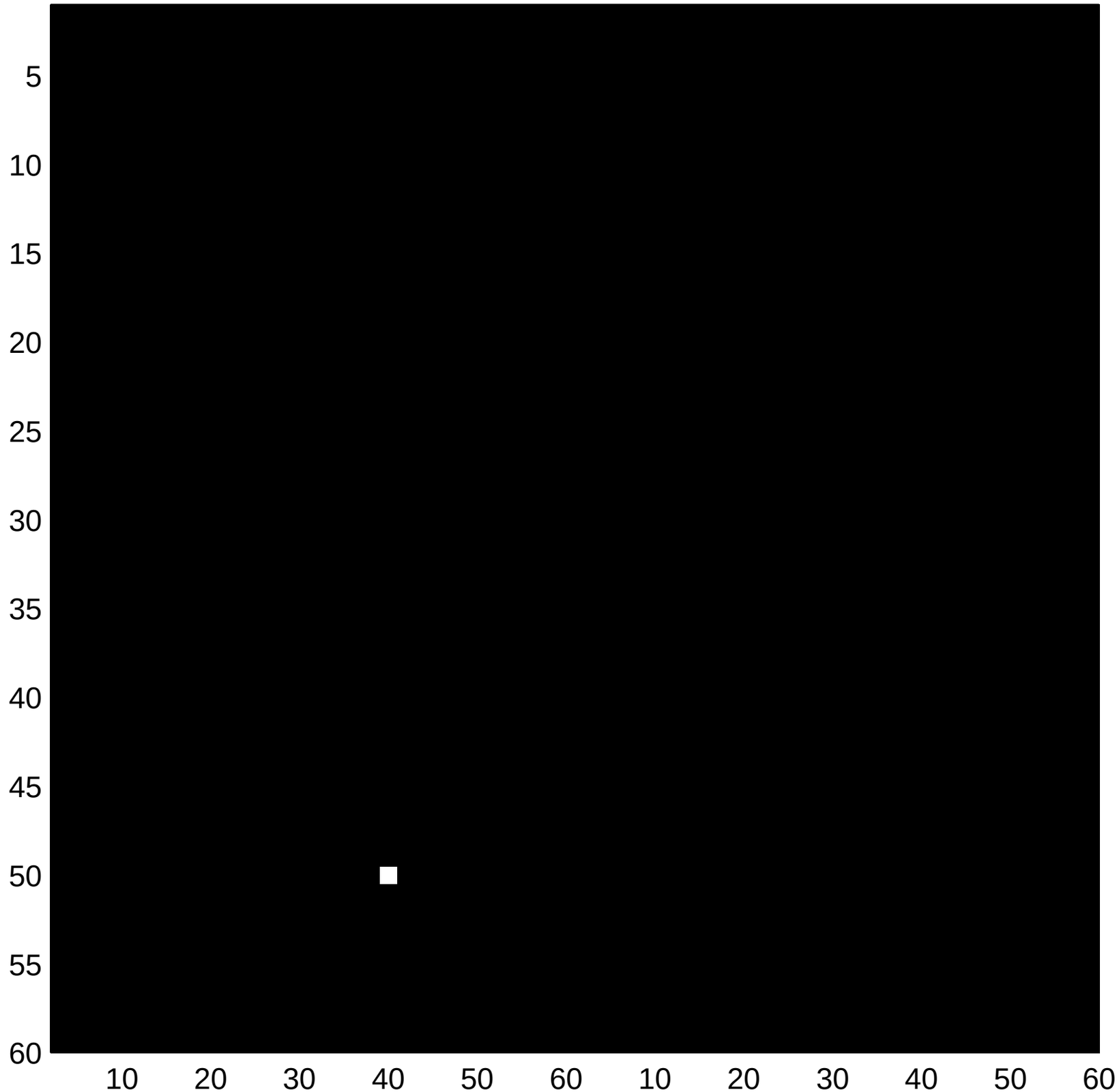
(x,y) space



(k,q) space




y
R
θ
x


5
10
15
20
25
30
35
40
45
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55
60
10
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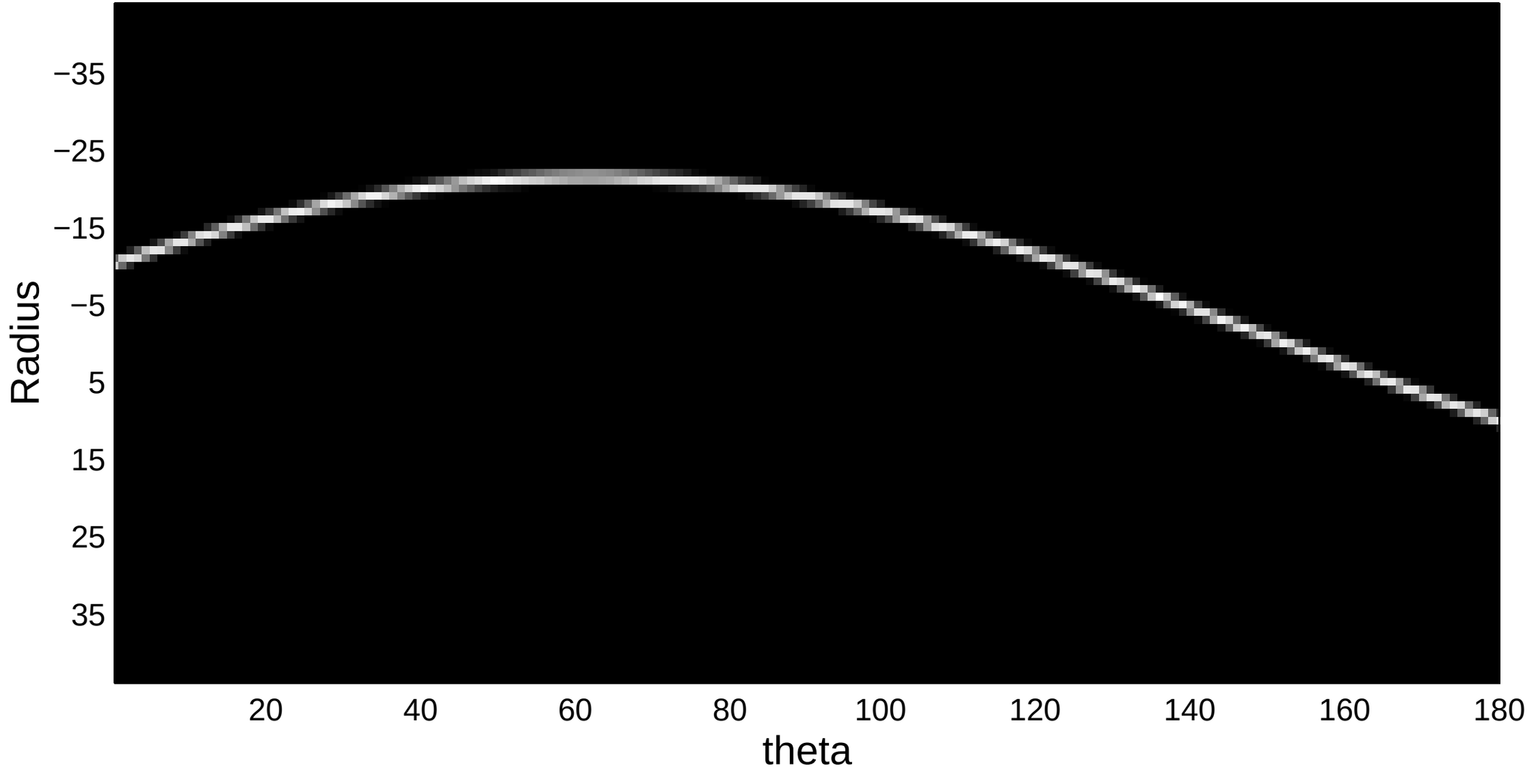
60
10
20
30
40
50
60


−35
−25
−15
−5
5
15
25
35
Radius
20
40
60
80
100
120
140
160
180
theta