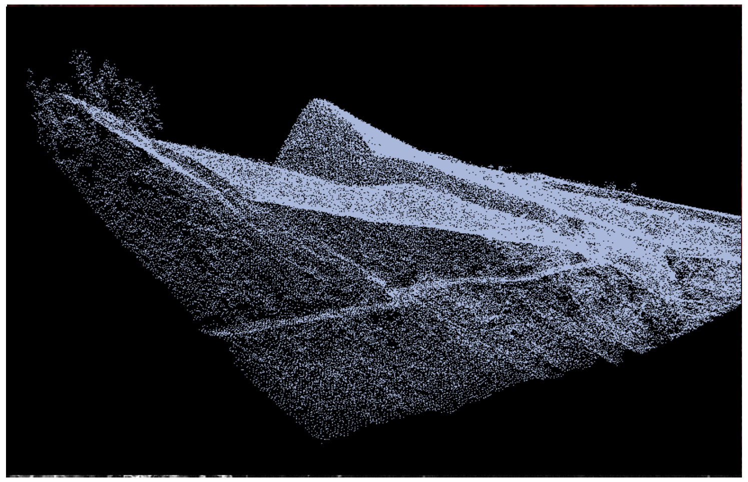
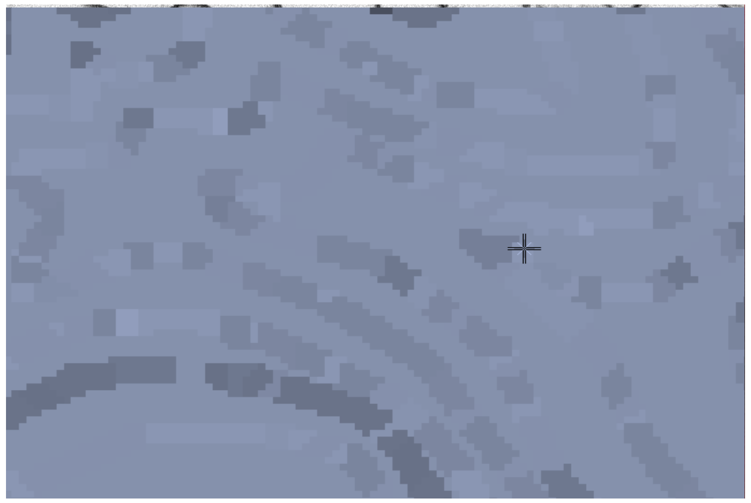
IMAGE SEGMENTATION

IMAGE AND VIDEO PROCESSING – MODULE 1





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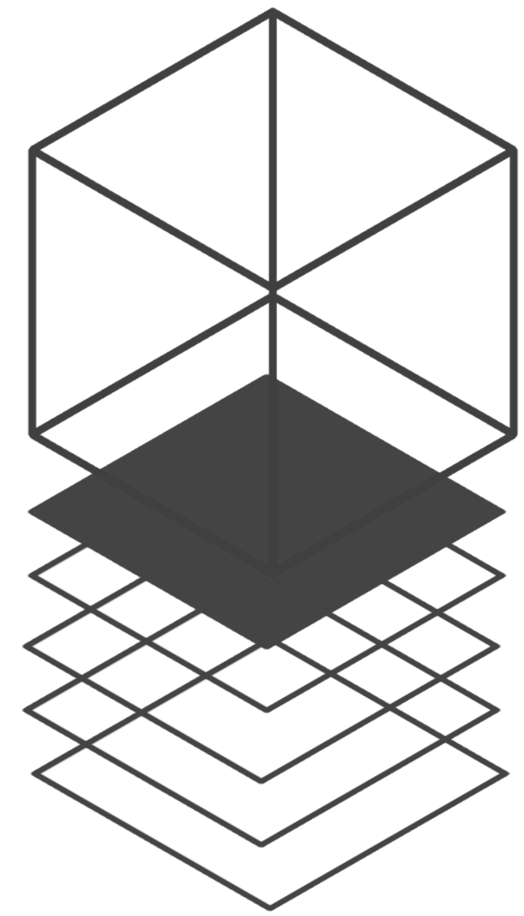
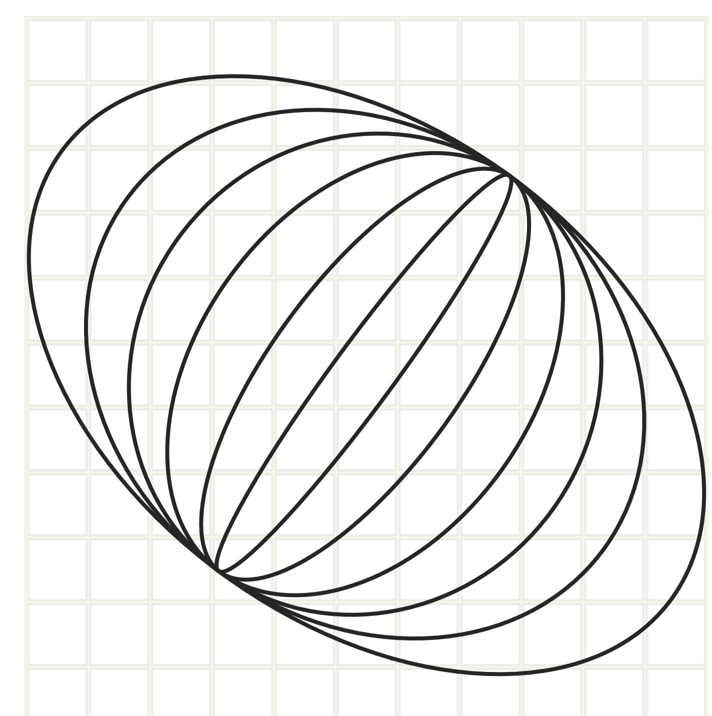
OBJECTIVES

- Compare the different segmentation techniques in image processing and account for their strengths and weaknesses
- Explore how bin sizes affects the nonparametric estimation in segmenting ROI from images



KEY TAKEAWAYS

- Thresholding is useful in image segmentation since it is the simplest way to separate blobs or cells of interest from the background
- Parametric segmentation is probabilistic as it takes the Gaussian distribution function as its pixel membership algorithm
- Nonparametric segmentation is dependent on the bin sizes and works best for images where the color distribution is uneven



SOME PITFALLS

- Segmenting grayscale images through thresholding might not work for some images where different shades and chromaticity of such color is present in the background

IMAGE SEGMENTATION

In the previous activity, we have made use and took advantage of ImageJ in segmenting our images. However, it is of utmost importance to learn the basics of **image segmentation** and the process of automating it since it helps us efficiently gather training data for **machine learning** in the case of repetitive imaging experiments where ImageJ becomes cumbersome to use. In this activity, we investigate how image segmentation works as well as the methods to segment an object of interest from an image.

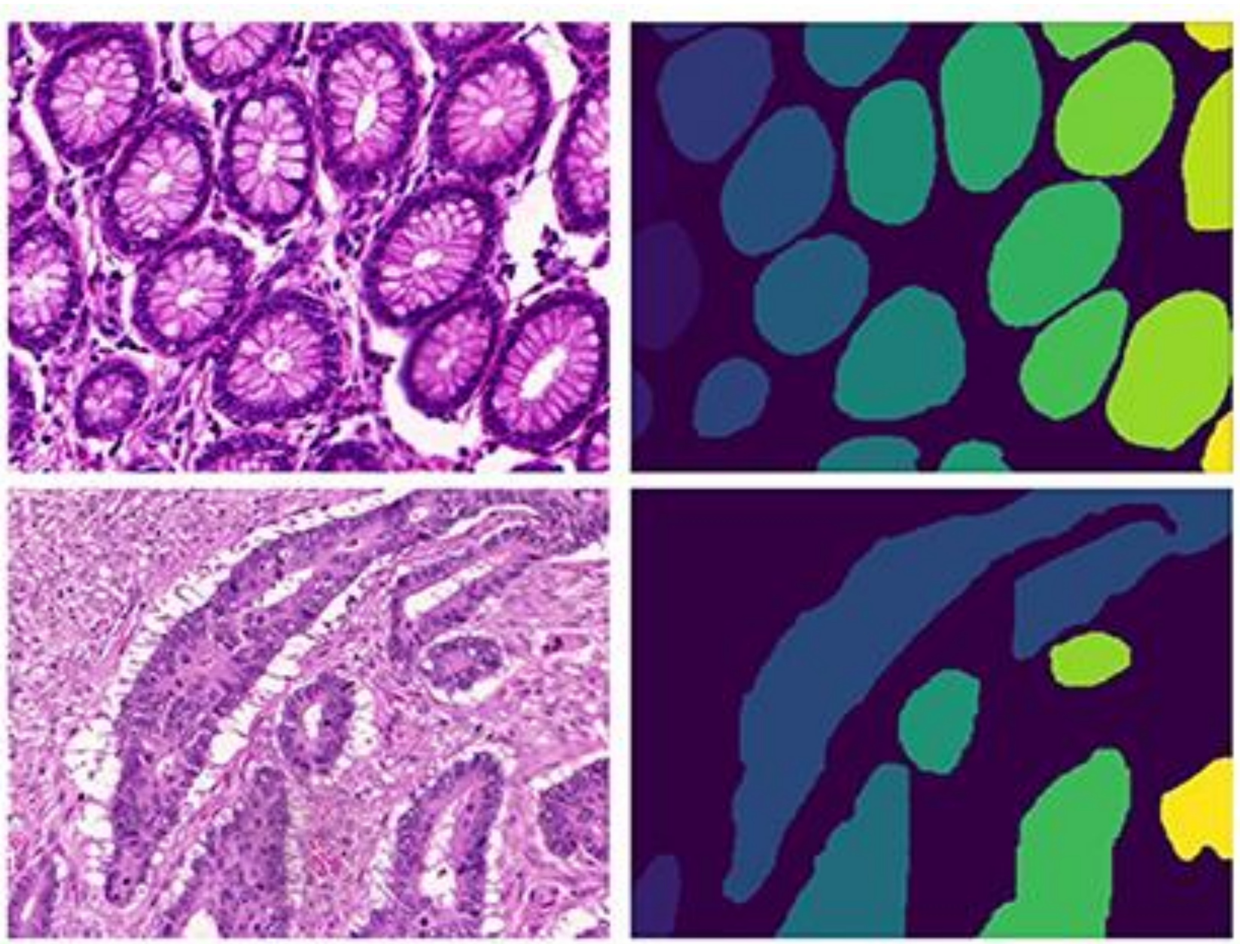


Figure 1. This Photo by Unknown Author is licensed under CC BY

In principle, image segmentation involves the picking of a **region of interest (ROI)** out from the rest of the image such that further processing can be done to it – such as morphological operations and blob analysis – which are the focus of the next activities in the course. This segmenting process take on a given **selection rules** based on the features unique to such ROI.

SEGMENTATION BY THRESHOLDING

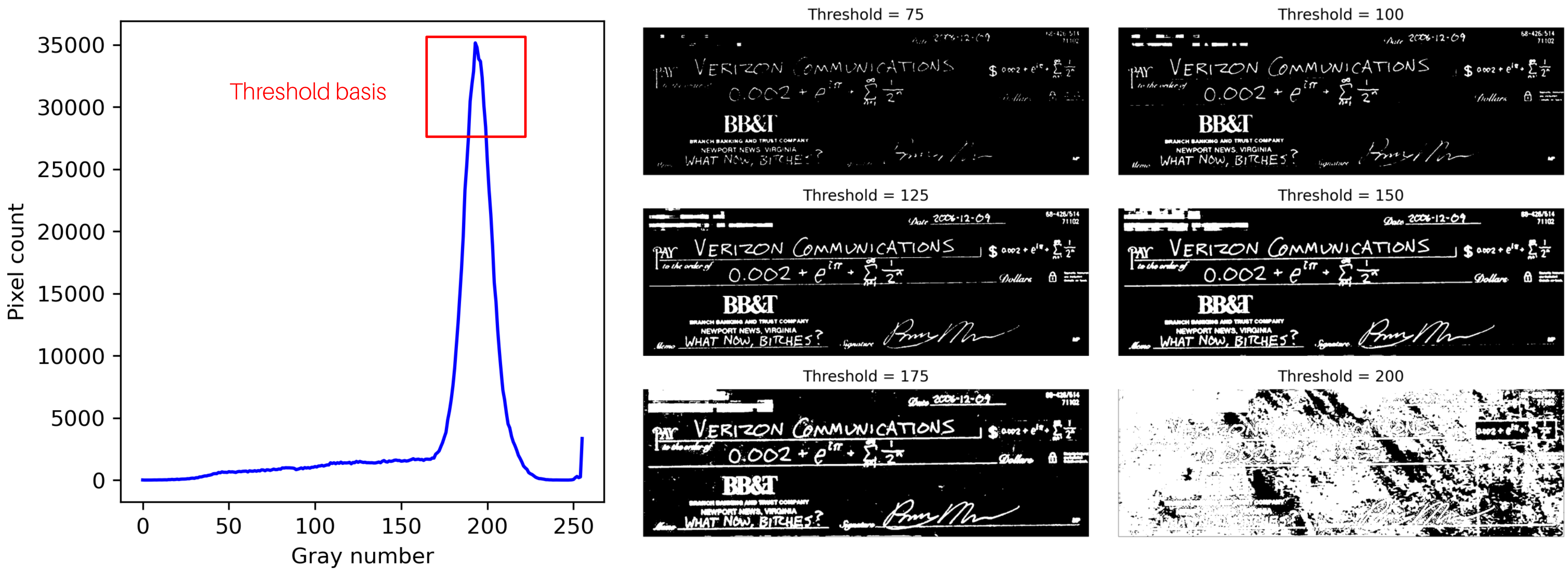


Figure 2. Segmentation by thresholding of a sample image of a cheque.

For grayscale images, segmentation can be done through thresholding if the ROI has a **distinct grayscale range** from the background. In the image, the ROI is the text written on the cheque. Basically, this segmentation technique is straightforward since a specific **gray value will act as a cut-off**, hence, a threshold for our image! In the histogram, the peak at around 200 gray number implies that the most dominant color in the image is the **background** (close to white) and **clipping the histogram** at values above it will result to the script being segmented from the image.

LIMITATIONS OF THRESHOLDING

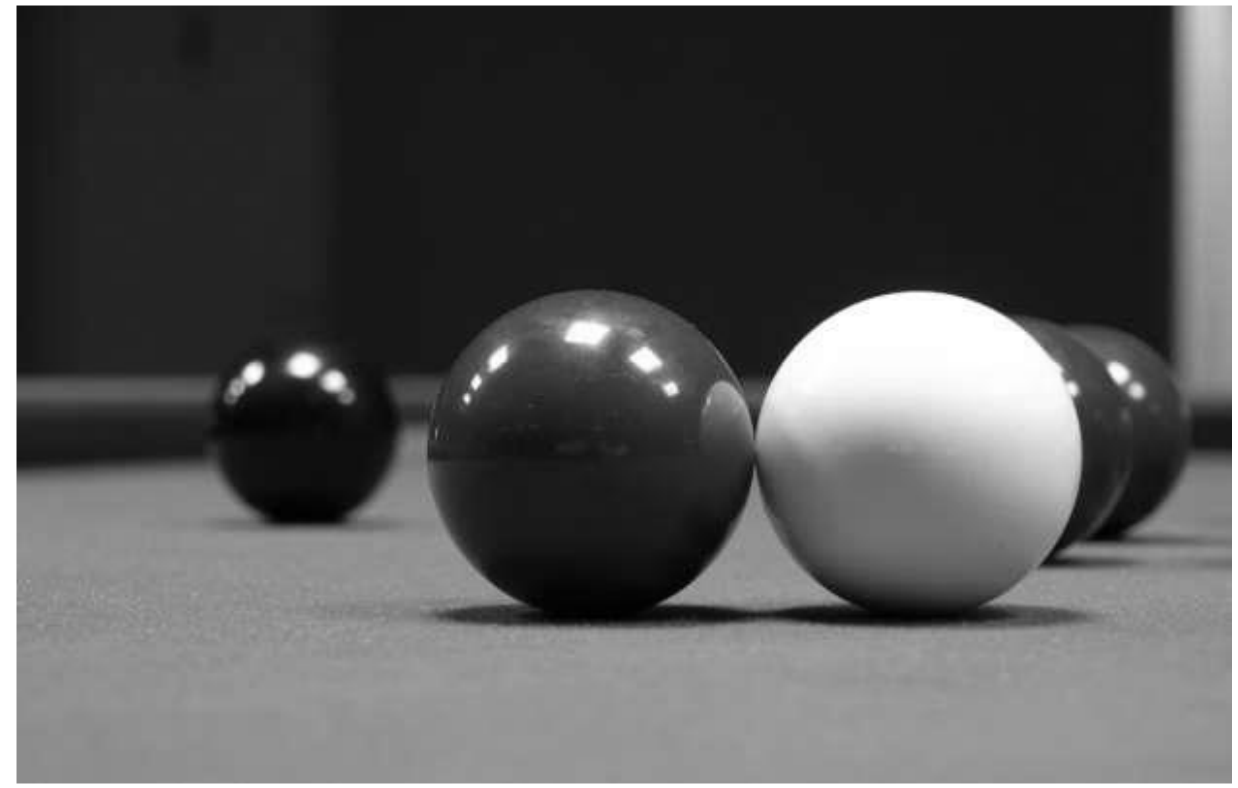



Figure 3. Sample image of colored billiard balls and its grayscale equivalent.

Segmenting regions of interest can easily be done through thresholding for grayscale images, but it also has its **limitations** as well. If we were to consider the image of colored balls, and say for example, we want to segment the red ball, it is almost impossible to do it in grayscale since the red ball has the same grayscale value as the background upon conversion. In practice, 3D objects in general will always have **shading variations** to it where different brightness of the same color must be considered. For this reason, it is imperative to separate **brightness and chromaticity** information of our ROIs into a new **color space**.

NORMALIZED CHROMATICITY

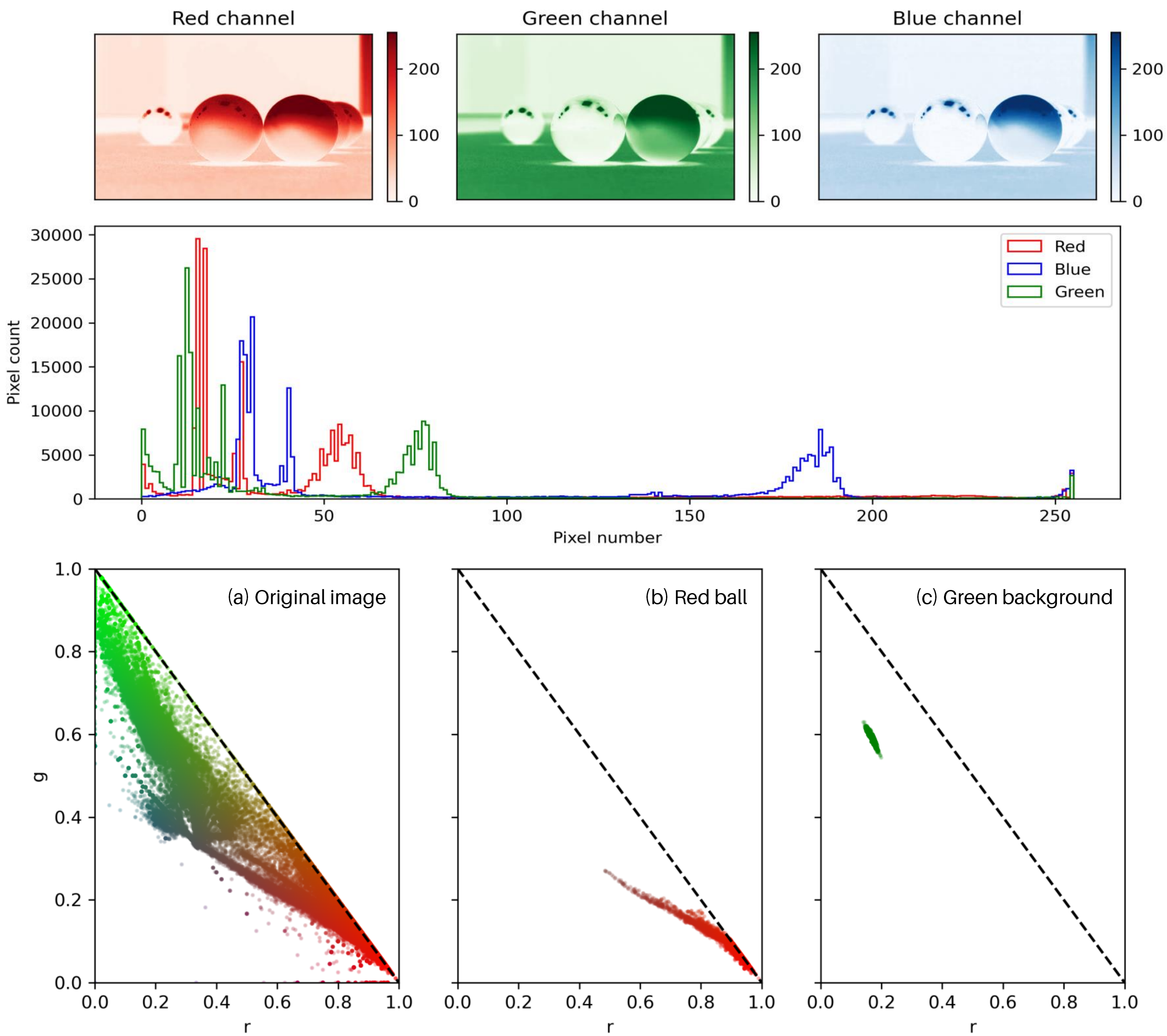


Figure 4. Histogram of the RGB channels and NCC of the original image from Figure 3.

Looking at the histogram of the billiard balls, the RGB image has a **continuous distribution** of the color intensities across the range of pixel numbers below 100. The RGB channels tend to **peak** at values near 0 due to the dark background that dominates the image itself.

Interestingly, the **normalized chromaticity coordinates (NCC)** of the RGB image, the red ball, and green background were investigated. This basically transforms the 3D RGB color space to a **two-dimensional space** represented by r and g – where the chromatic information is stored. As expected, the NCC of the red ball tend to occupy a small blob in the red region regardless of its **shading variations**.

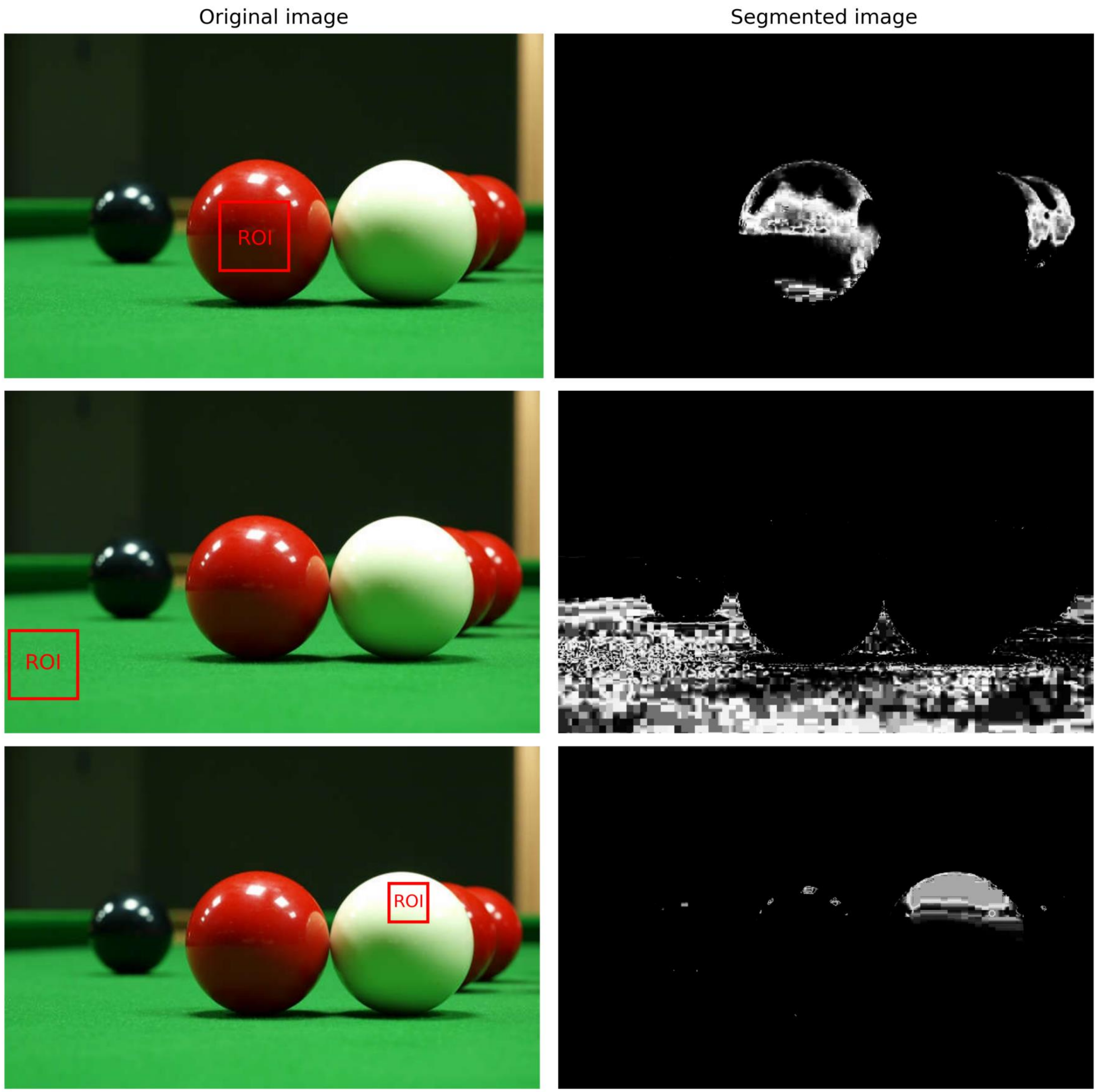


Figure 5. Parametric segmentation on the billiard balls for varying ROIs.

PARAMETRIC SEGMENTATION

This technique assumes a **Gaussian probability distribution** given by

$$p(\mathbf{x}) = \frac{1}{\sigma_{\mathbf{x}}\sqrt{2\pi}} \exp\left[-\frac{\mathbf{x}-\mu_{\mathbf{x}}}{2\sigma_{\mathbf{x}}^2}\right]$$

in tagging a pixel as belonging to a region of interest or not such that the probability of that pixel belonging to the color of the ROI is quantified. By taking the **mean and standard deviation** of the pixels contained in the ROI and comparing it to the normalized chromaticity of the original image, the **joint probability** of r and g test the likelihood of the pixel membership to the ROI and the resulting quantity is the segmented image itself.

NONPARAMETRIC SEGMENTATION

In principle, nonparametric segmentation is **computationally faster** as no computations are needed, just a look-up at the histogram values. In this estimation, the **histogram** itself is used to tag the membership of pixels belonging to the image through **backprojection techniques**. This can be done by obtaining a **2D histogram** of the RGB values transform into the NCC space, and binning the image values in a matrix.

Effect of bin sizes. The bin sizes can be treated as the defining parameter for non-parametric segmentation. For varying bin sizes, it was perceived that the amount of pixel being tagged varies for increasing bin number – **larger bin sizes** mean **smaller bins** for the look-up table. This results to the segmentation or pixel tagging be **more specific**. This is why in smaller bins (5 to 10) yields a segmented image that includes some unwanted elements from the background!

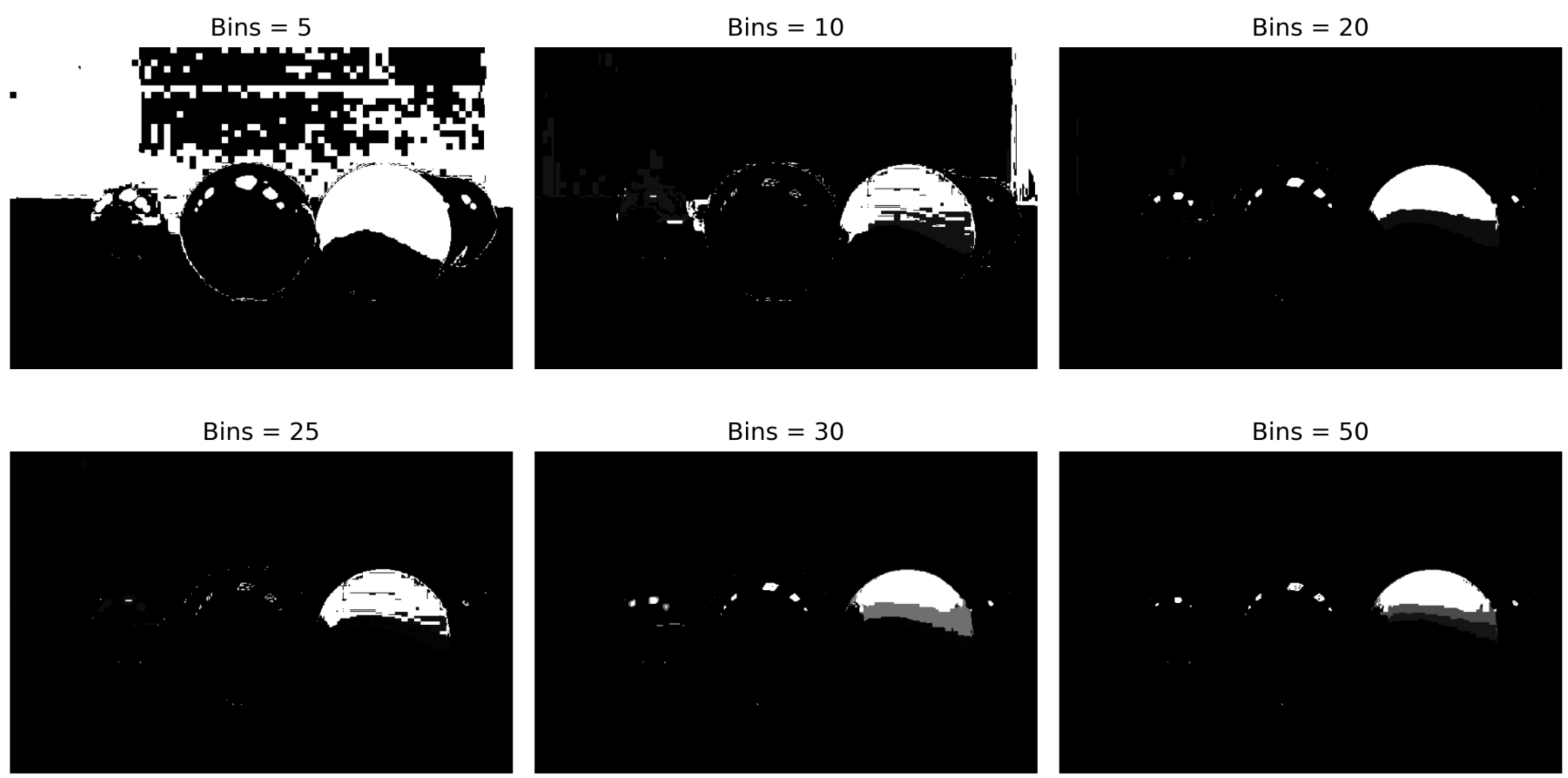
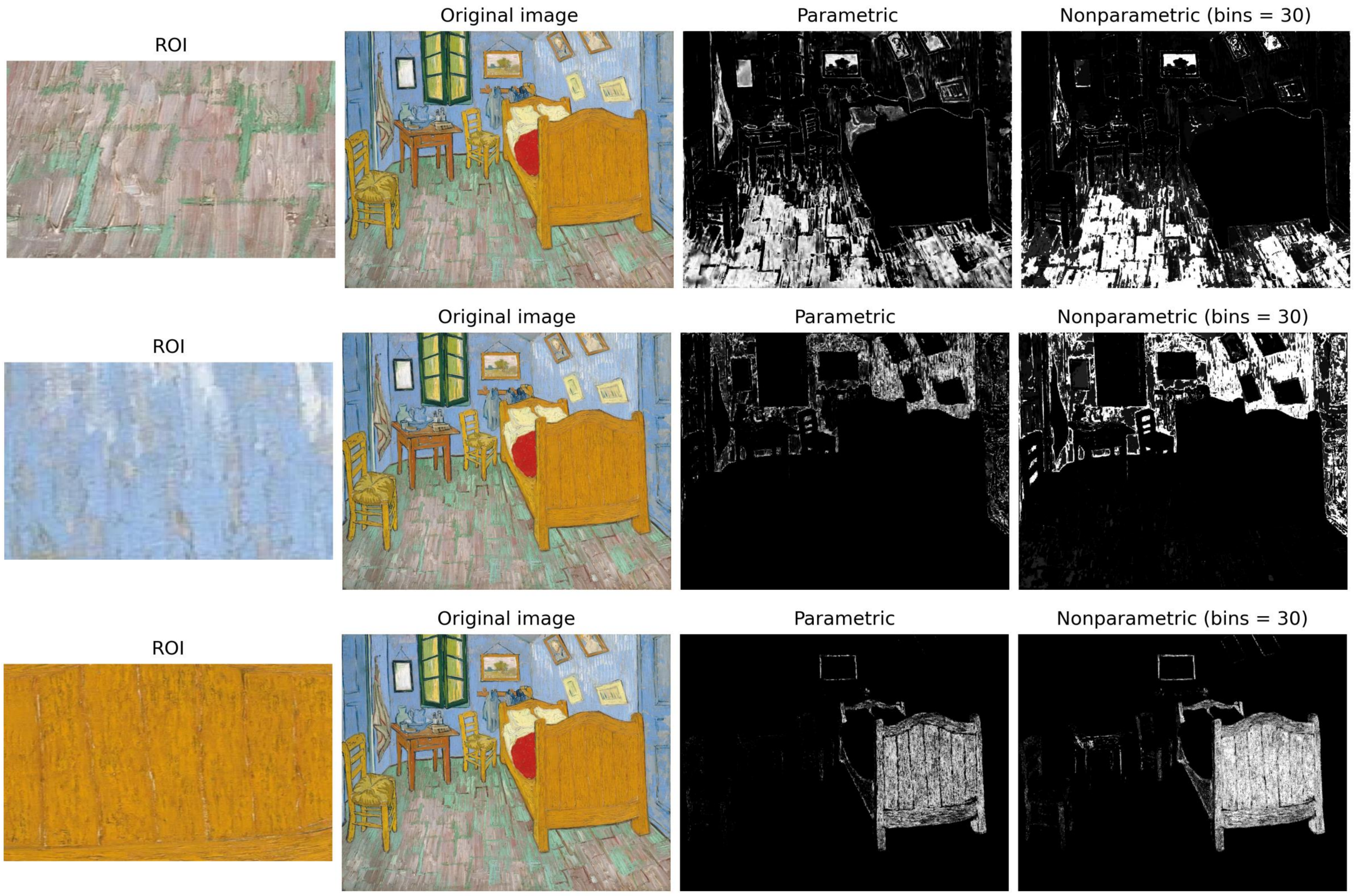


Figure 6. Nonparametric segmentation for varying bin sizes.

We experiment with some known paintings of Van Gogh such as the **The Bedroom** and compare how parametric and nonparametric segmentation algorithms differ.



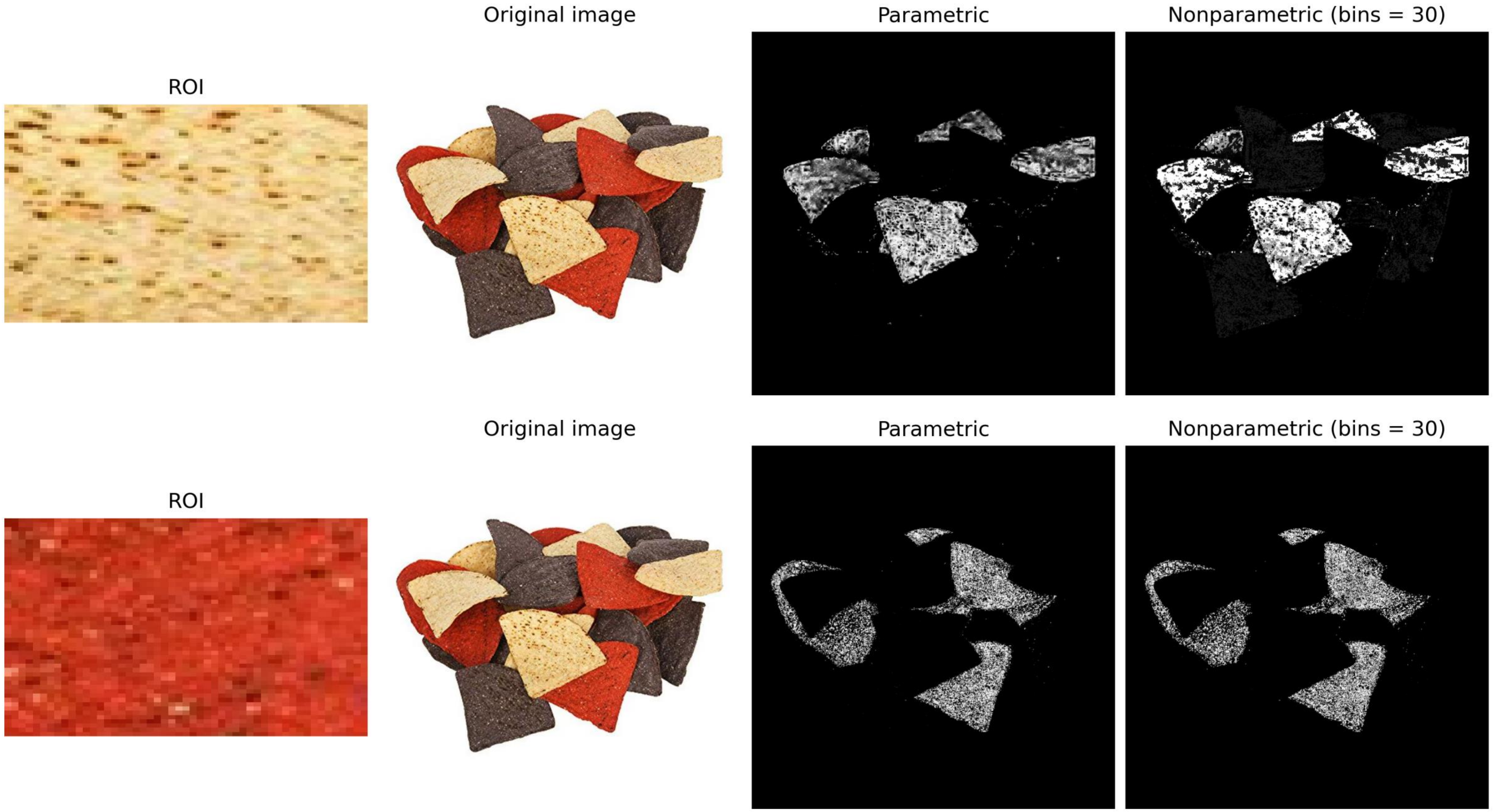
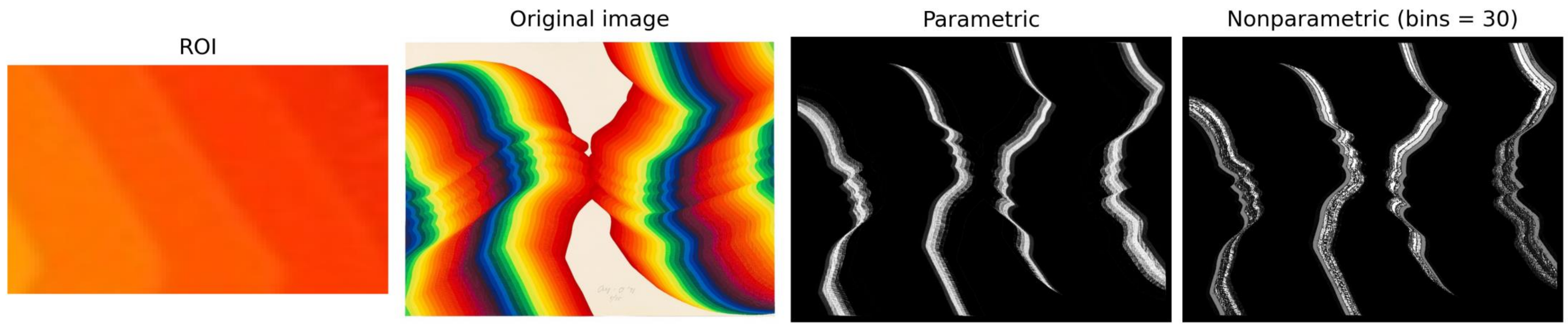


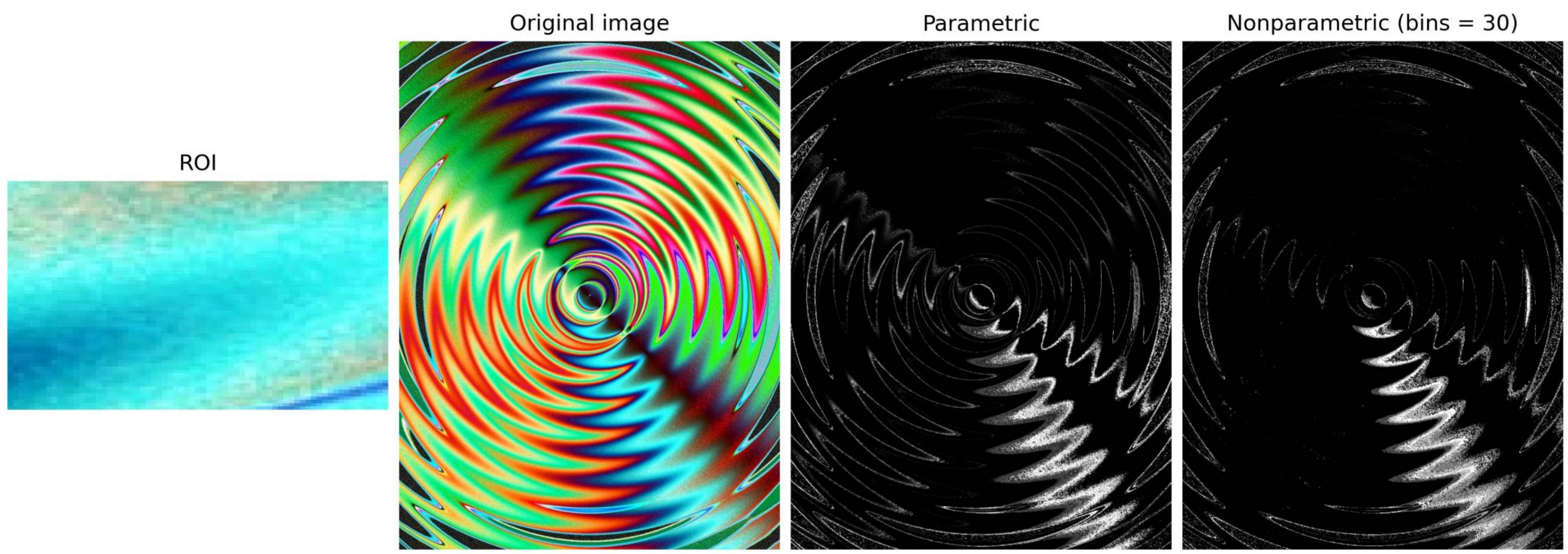
Figure 7. Comparison of the parametric and nonparametric segmentation using some colored chips.

For the light brown chips, some portions of the dark brown chips were tagged and segmented for the nonparametric estimation. This implies that **larger bin size** should be set to obtain a much-defined result as much as possible. Nonetheless, both techniques are quite similar for images that has a **distinct and clear contrast** in between colors and the background like the image of the chips used.

CONTINUOUS IMAGE AND ROI

For continuous color distributions in the image or ROIs, parametric segmentation tend to have some gradient in result – possibly due to its Gaussian parameters while the nonparametric method have shown discrete segmentation layers that is not as smooth as the parametric. This is because of the binning nature of the segmentation technique. Still, both techniques are worth comparing for continuous RGB images.





REFLECTION

I find the activity fun as I get to work and understand the algorithms behind image segmentation. While having ImageJ as a readily available application for segmenting images, nothing beats the feeling of having to know how to segment images from code and scratch! I was able to learn the different image segmentation techniques and account for the pitfalls that I have encountered in my codes. Overall, I would give myself a score of **110/100** !

REFERENCES | GITHUB

1. M. Soriano, Applied Physics 157 – Image Segmentation, 2023.