



# Image Analysis and Pattern Recognition

## SQUARE TILING PUZZLE

Group 44

June 2, 2023

**Input:** An 2000x2000 image with randomly arranged puzzle pieces

**Output:** Piece masks, feature maps and clustered pieces

**Objective:**

- Segment puzzle pieces
- Extract & filter different features
- Cluster pieces correctly



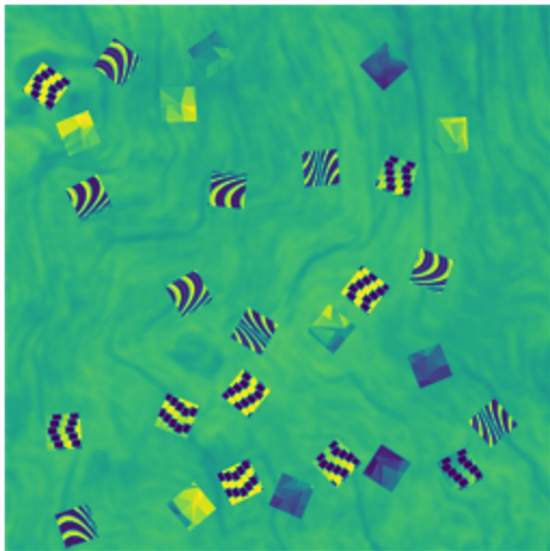
# Part 1 - Segmentation

- Applying a Sobel filter
- Identifying contours
- Refining contours
- Creating convex hulls
- Piece extraction

$$h_1 = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

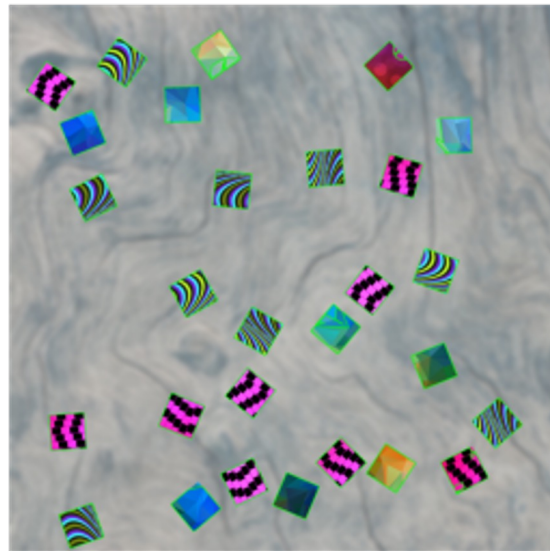
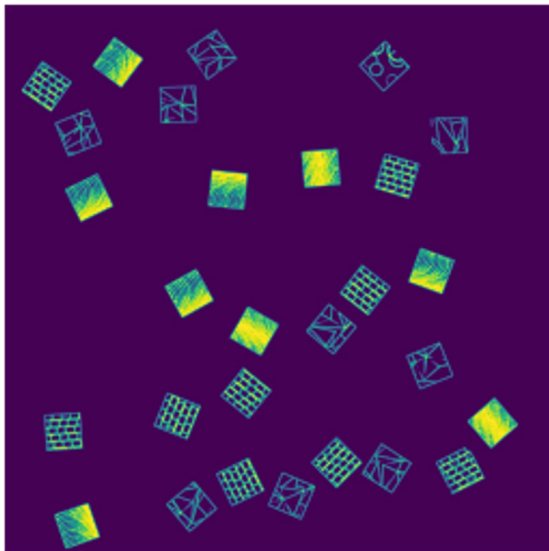
$$h_2 = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}$$

$$h_3 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$



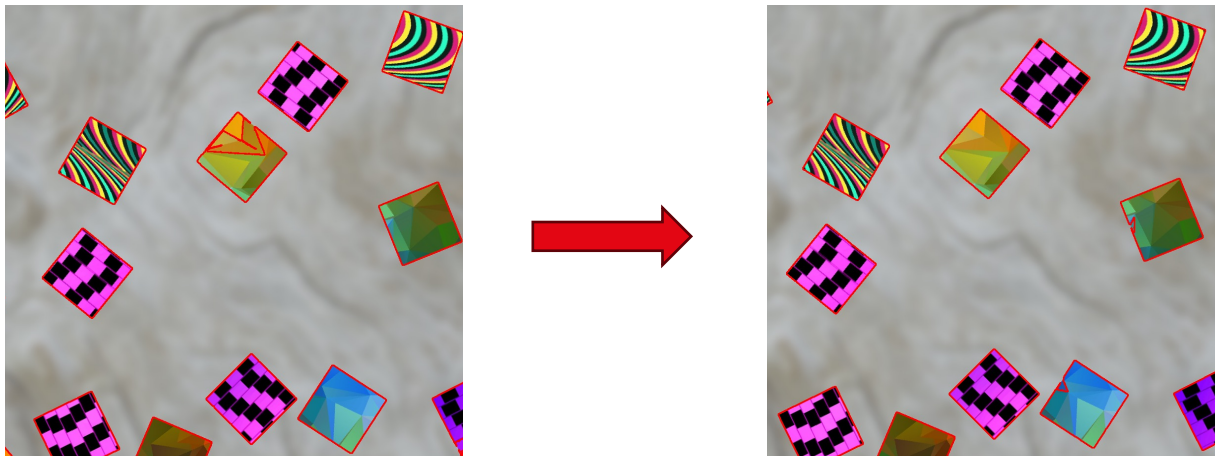
# Contour Identification

- Setting a threshold to the Sobel-processed image
- `cv2.findContours()`



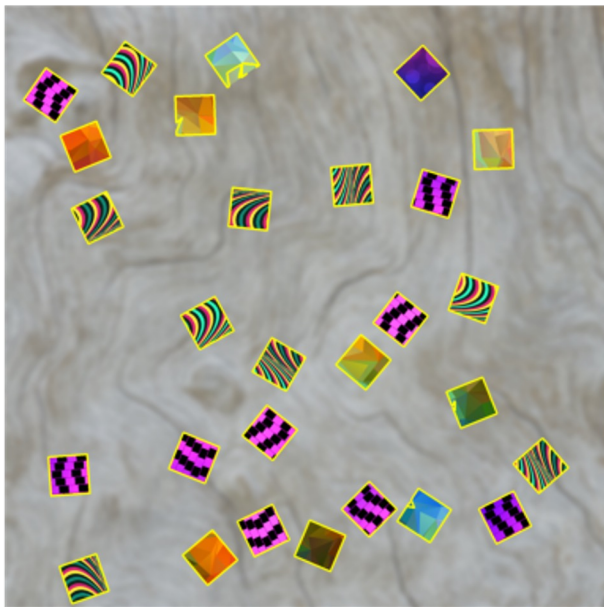
# Contour Refinement

- Filter:
  - Multiple overlaps, too small/large contours, non-square ones
- Check:
  - “Twin contours” – pairs of contours that have centroids close together



# Convex Hull Contours

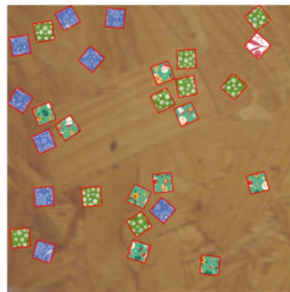
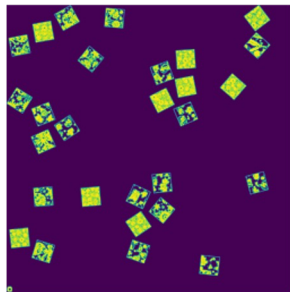
- Convex hull: the smallest convex polygon that contains all the points of the contour
- `cv2.convexHull()`





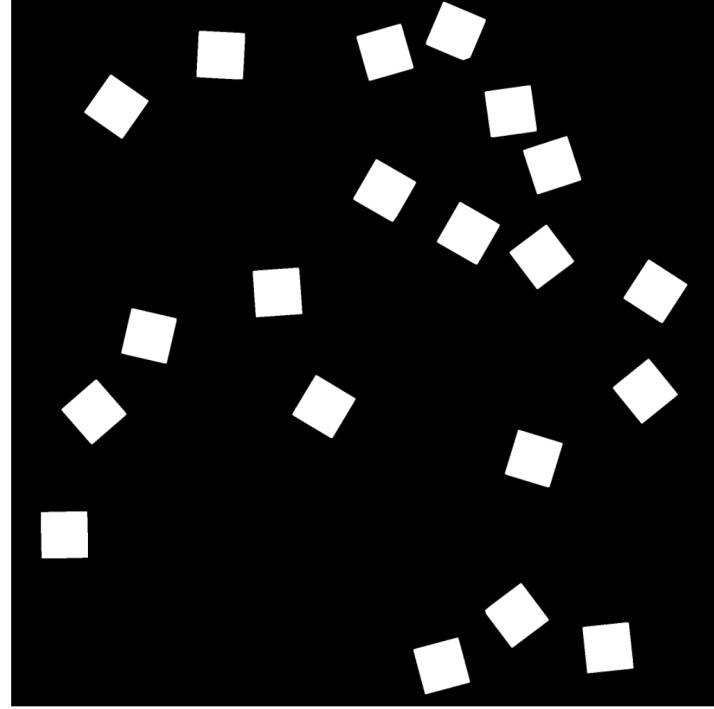
# Piece Extraction

- Calculate the minimum enclosing rectangle of each piece
- Calculate its rotation angle and rotate the whole image
- Calculate the bounding box, and crop!





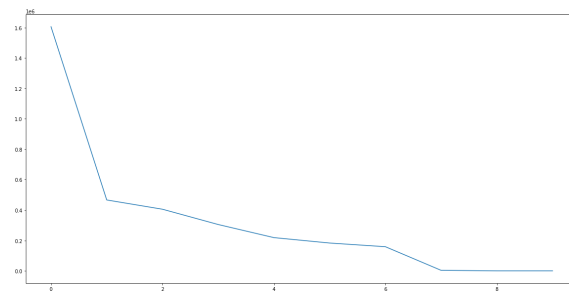
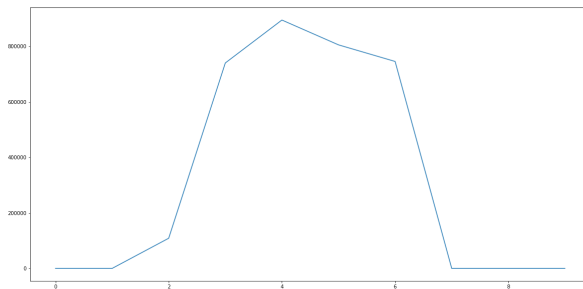
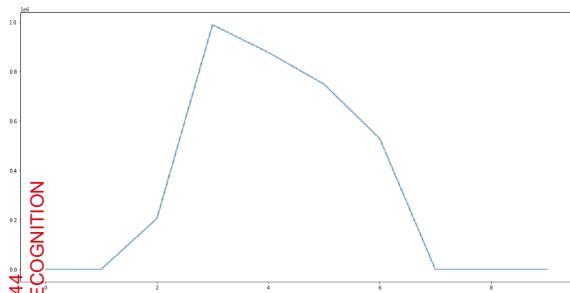
# Piece Mask Result



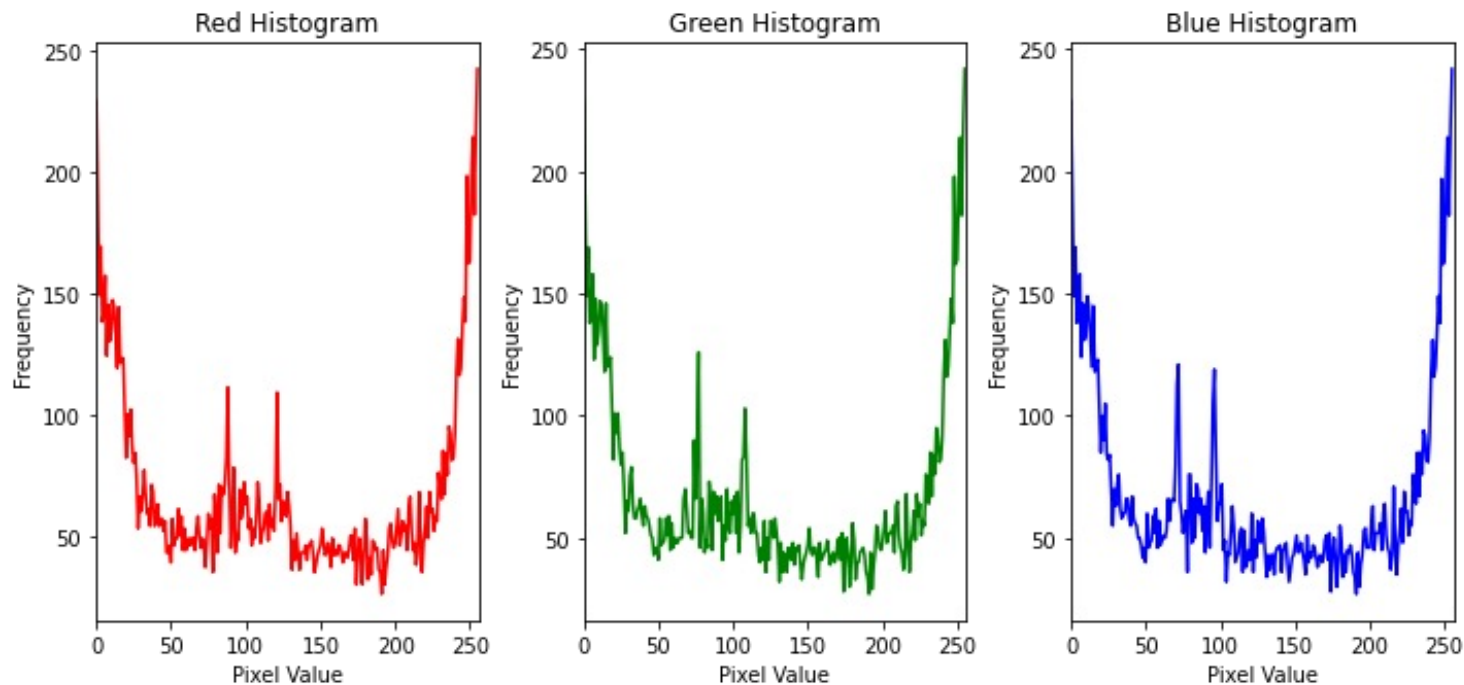
# Part 2: Feature Extraction

- Gabor filters
- Color histograms

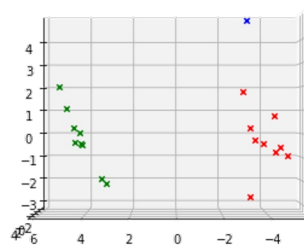
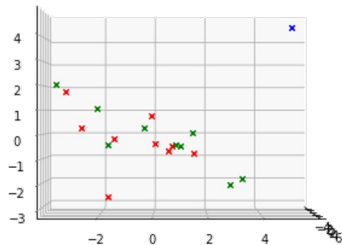
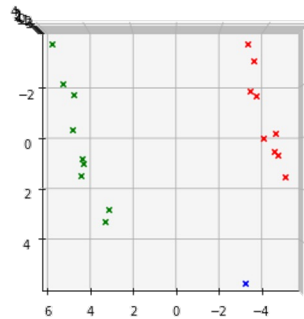
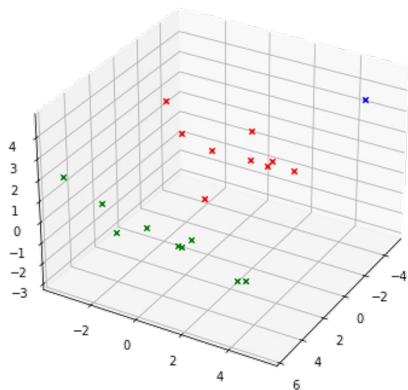
$$gb(x, y) = \exp \left( -\frac{1}{2} \left( \frac{x_\theta^2}{\sigma^2} + \frac{y_\theta^2}{(\Gamma\sigma)^2} \right) \right) \cos \left( \frac{2\pi}{\lambda} x_\theta + \psi \right)$$



# Color Histogram



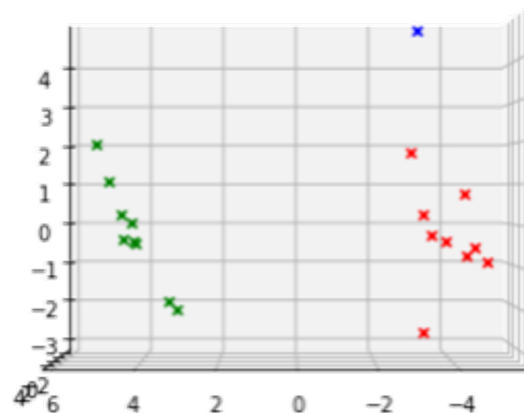
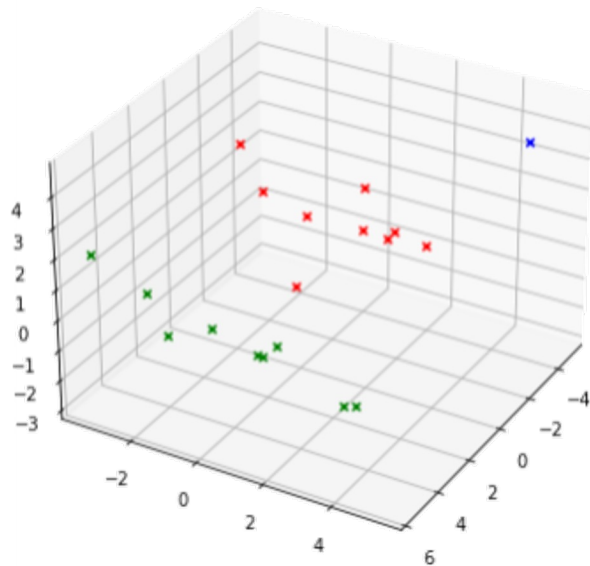
# Feature Extraction Result: Principal Component Analysis (PCA)



# Part 3: Clustering

- KMeans Clustering
- Inertia and Silhouette Scores
- Determining the Optimal Number of Clusters
- Removal of Outliers & Combination of Similar Clusters

# KMeans Clustering





## ■ Inertia

- measures the sum of squared distances of samples to their closest cluster center. We want to minimize this.

$$\sum_{i=1}^n \min_{j=1}^k |x_i - c_j|^2$$

## ■ Silhouette Score

- measures how close each sample in one cluster is to the samples in the neighboring clusters. We want to maximize this.

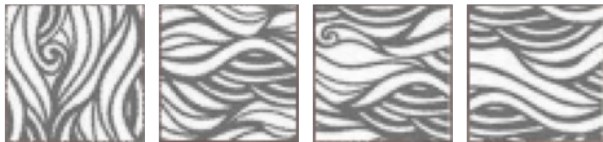
$$s_i = \frac{b_i - a_i}{\max(b_i, a_i)} \quad b_i = \min_{k \neq i} \frac{1}{|C_k|} \sum_{j \in C_k} d(i, j) \quad a_i = \frac{1}{|C_i| - 1} \sum_{j \in C_i, i \neq j} d(i, j)$$

# Determining the Optimal Number of Clusters

- Normalizing and combining multiple metrics: Silhouette, Inertia
- The optimal number of clusters is then chosen to be the number that maximizes this combined score.

# Removal of Outliers & Combination of Similar Clusters

Cluster 1

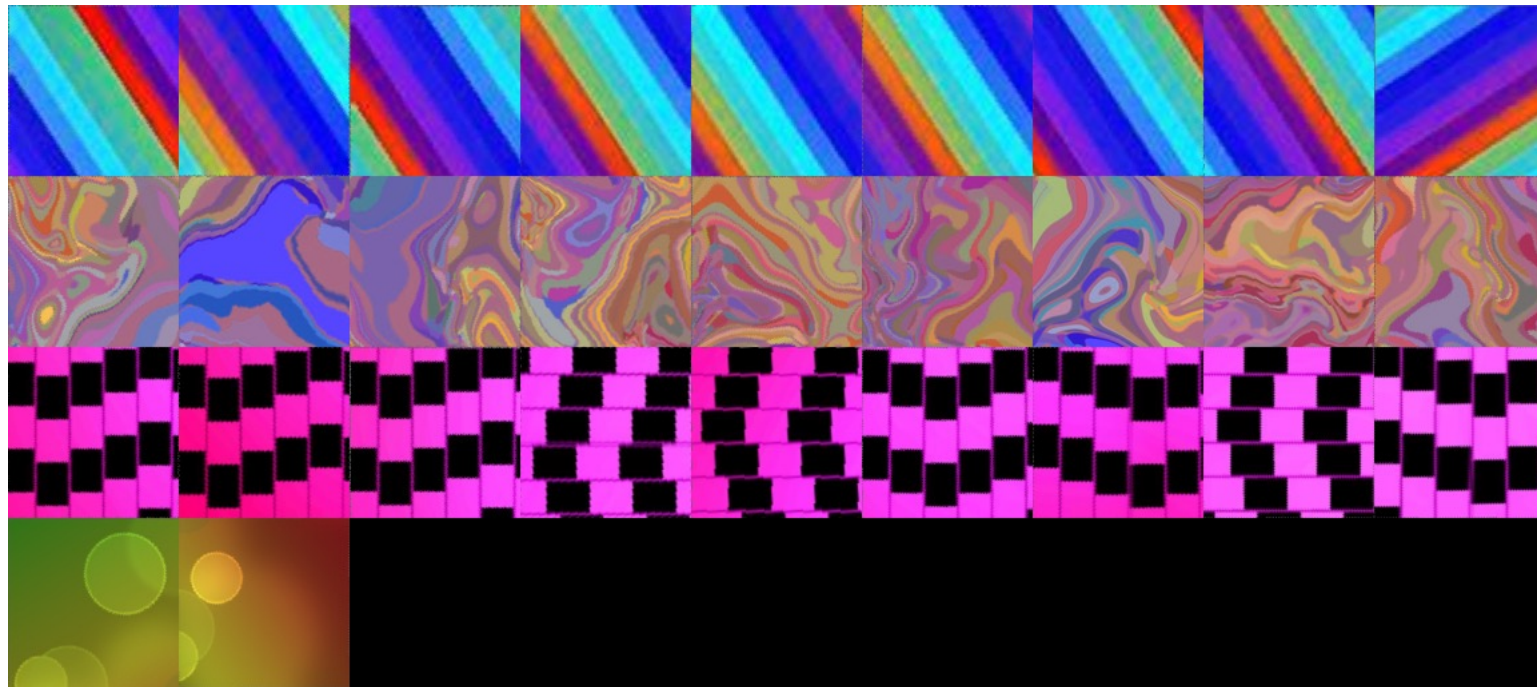


Cluster 3



# Our Results

- 70 ~ 80% accurate



- Applying more preprocessing steps before the feature extraction
- Feature selection?
- Applying more filters to extract more efficient and informative features

