# Image Preprocessing

### Noise reduction

Gaussian, median, bilateral filtering

### Contrast enhancement

Stretching, adaptive methods

### Histogram equalization

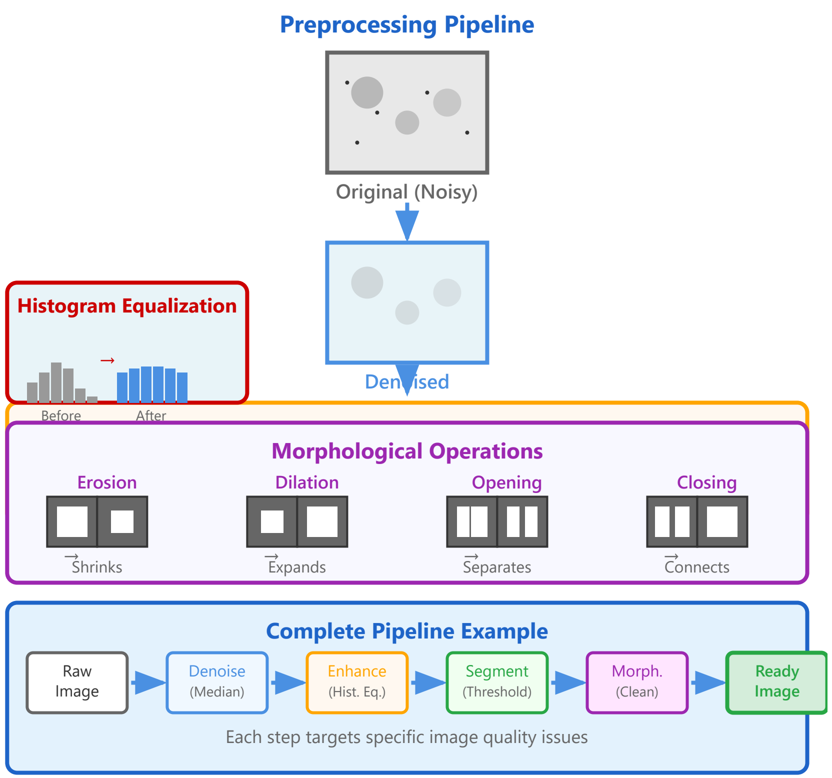
Uniform intensity distribution

### Morphological operations

Erosion, dilation, opening, closing

### Registration basics

Aligning multiple images

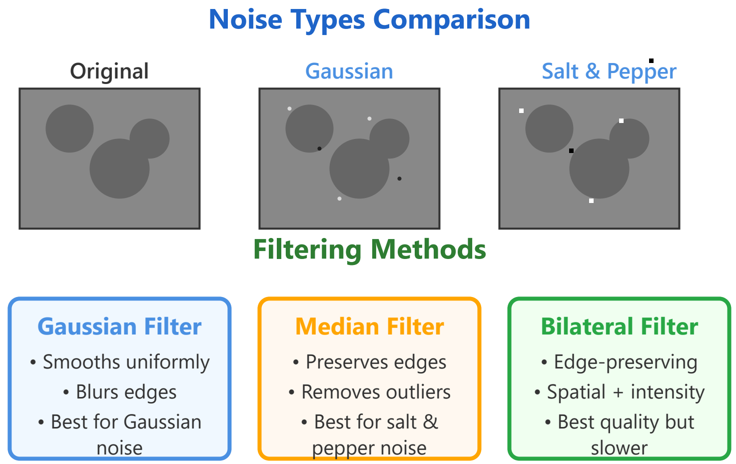


# 1. Noise Reduction

Noise reduction is a fundamental preprocessing step that removes unwanted random variations in pixel intensities. Image noise can originate from various sources including sensor limitations, poor lighting conditions, electronic interference, and transmission errors.

### Common Noise Types:

- **Gaussian Noise:** Random variations following normal distribution
- **Salt-and-Pepper Noise:** Random white and black pixels
- **Poisson Noise:** Signal-dependent noise from photon counting
- **Speckle Noise:** Multiplicative noise common in radar/ultrasound




## Filter Details

**Gaussian Filter:** Applies weighted averaging using a Gaussian kernel. The weight decreases with distance from the center pixel, creating a smooth blur effect. Excellent for reducing Gaussian noise but can blur important edges.

$$G(x,y) = (1/(2\pi\sigma^2)) \times e^{(-(x^2+y^2)/(2\sigma^2))}$$

**Median Filter:** Replaces each pixel with the median value of neighboring pixels. Non-linear operation that effectively removes impulse noise while preserving edges better than Gaussian filtering.

**Bilateral Filter:** Combines spatial and intensity information. Smooths regions with similar intensities while preserving sharp edges. Computationally more expensive but produces superior results for edge preservation.

### Practical Applications:

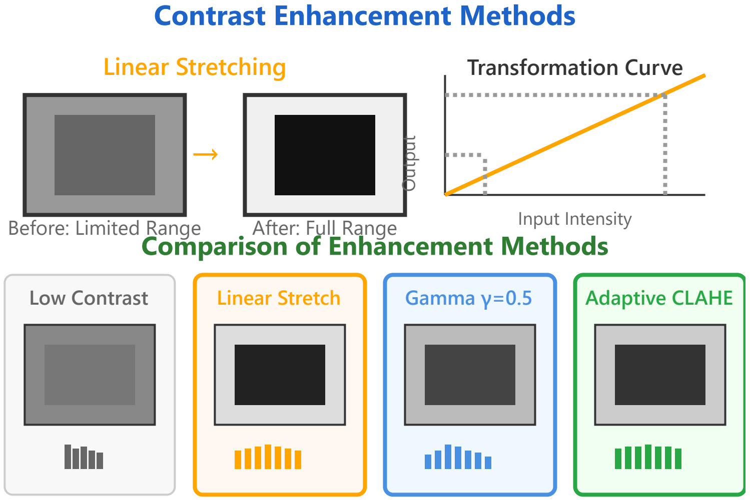
Medical imaging (MRI, CT scans), astronomical photography, surveillance systems, smartphone cameras (computational photography), and any scenario where sensor noise degrades image quality.

# 2. Contrast Enhancement

Contrast enhancement improves the visual quality of images by expanding the range of intensity levels. Images captured in poor lighting conditions or with limited dynamic range often appear washed out or too dark, making features difficult to distinguish.

### Main Techniques:

- **Linear Stretching:** Maps original intensity range to full available range
- **Piecewise Linear:** Different stretching for different intensity regions
- **Gamma Correction:** Non-linear adjustment for display devices
- **Adaptive Methods:** Local contrast enhancement based on neighborhood




## Detailed Method Descriptions

**Linear Contrast Stretching:** The simplest method that maps the minimum and maximum intensities in the image to the full available range (typically 0-255 for 8-bit images). Formula: Output = (Input - Min) × (255 / (Max - Min))

**Gamma Correction:** Applies a non-linear power-law transformation. Values of $\gamma < 1$ brighten dark regions, while $\gamma > 1$ darkens bright regions. Essential for compensating display device characteristics and human perception.

```
Output = Input^γ, where γ is the correction factor
```

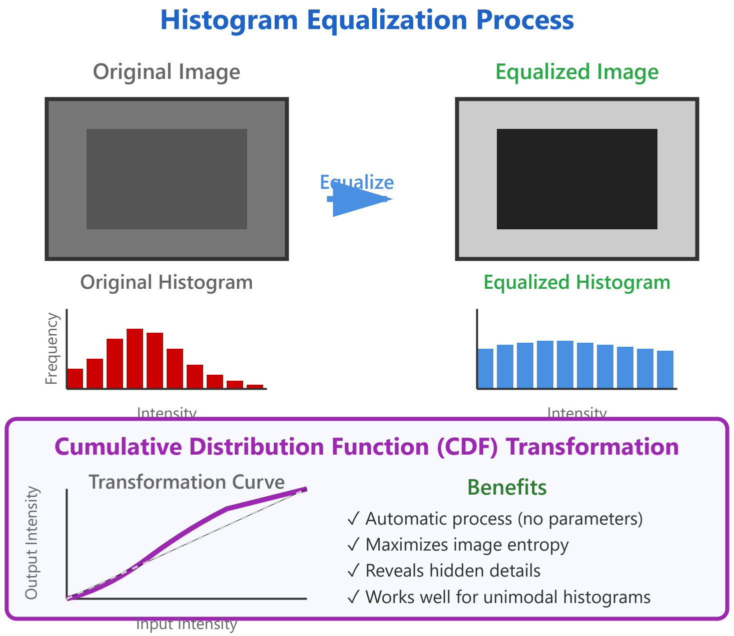
**CLAHE (Contrast Limited Adaptive Histogram Equalization):** Divides the image into small tiles and applies histogram equalization to each tile separately. Limits contrast enhancement to prevent noise amplification. Superior for images with varying local contrast.

### Practical Applications:

Medical imaging (X-rays, mammography), underwater photography, satellite imagery analysis, low-light photography enhancement, document image processing, and any scenario requiring improved visual interpretation of details.

# 3. Histogram Equalization

Histogram equalization is a powerful technique that redistributes pixel intensities to achieve a more uniform distribution across the entire intensity range. Unlike simple contrast stretching, it considers the frequency distribution of intensities and aims to maximize image entropy.




### Key Concepts:

- **Histogram:** Graphical representation of pixel intensity distribution
- **Cumulative Distribution:** Running sum of histogram values
- **Transform Function:** Maps original to equalized intensities
- **Global vs. Local:** Applied to entire image or local regions

```
h(v) = number of pixels with intensity v
CDF(v) = Σ h(i) for i = 0 to v
Output(v) = round((CDF(v) - CDF_min) × (L-1)
/ (M×N - CDF_min))
```

## Algorithm Steps

**Step 1:** Calculate the histogram of the input image, which shows the frequency of each intensity level from 0 to 255 (for 8-bit images).

**Step 2:** Compute the cumulative distribution function (CDF) by summing the histogram values progressively. The CDF represents the probability that a pixel has an intensity less than or equal to a given value.

**Step 3:** Normalize the CDF to the full intensity range (0-255). This creates the transformation function that maps original intensities to new equalized intensities.

**Step 4:** Apply the transformation to each pixel in the original image using the normalized CDF as a lookup table.

### Advantages and Limitations:

- **Advantages:** Fully automatic, no parameter tuning required, effective for low-contrast images, reveals hidden details in shadows and highlights
- **Limitations:** May over-enhance noise, can create artifacts in images with bimodal histograms, may produce unnatural-looking results for some images

### Practical Applications:

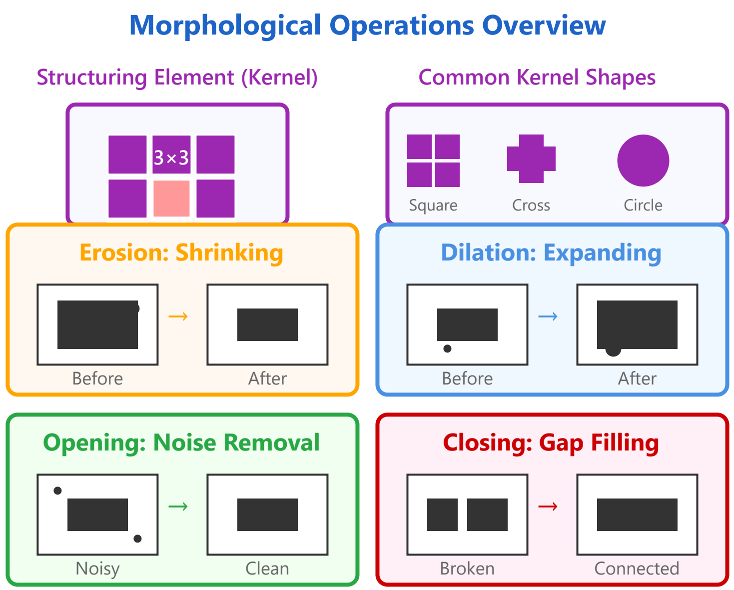
Medical image enhancement (X-rays, CT scans), astronomical image processing, remote sensing and satellite imagery, document scanning and OCR preprocessing, surveillance video enhancement, and scientific visualization.

# 4. Morphological Operations

Morphological operations are shape-based image processing techniques that operate on the geometric structure of objects in binary or grayscale images. These operations use a structuring element (kernel) to probe and modify the shape of features in the image.

### Fundamental Operations:

- **Erosion:** Shrinks bright regions, removes small objects
- **Dilation:** Expands bright regions, fills small holes
- **Opening:** Erosion followed by dilation (removes noise)
- **Closing:** Dilation followed by erosion (fills gaps)




## Detailed Operations

**Erosion:** The structuring element slides across the image. At each position, if all pixels under the kernel match the foreground, the center pixel remains; otherwise, it becomes background. This operation shrinks objects, removes small protrusions, and separates connected components.

**Dilation:** The opposite of erosion. If any pixel under the kernel matches the foreground, the center pixel becomes foreground. This operation expands objects, fills small holes, and connects nearby components.

**Opening:** Erosion followed by dilation with the same structuring element. Removes small bright objects (noise) while preserving the shape and size of larger objects. Effective for removing isolated bright pixels without significantly affecting larger structures.

**Closing:** Dilation followed by erosion. Fills small dark holes and connects nearby bright regions while maintaining object boundaries. Useful for closing gaps in contours and smoothing object boundaries.

### Advanced Morphological Operations:

- **Morphological Gradient:** Difference between dilation and erosion, highlights object boundaries
- **Top Hat:** Difference between input and opening, extracts bright objects on dark background
- **Black Hat:** Difference between closing and input, extracts dark objects on bright background
- **Hit-or-Miss:** Template matching for finding specific patterns

### Practical Applications:

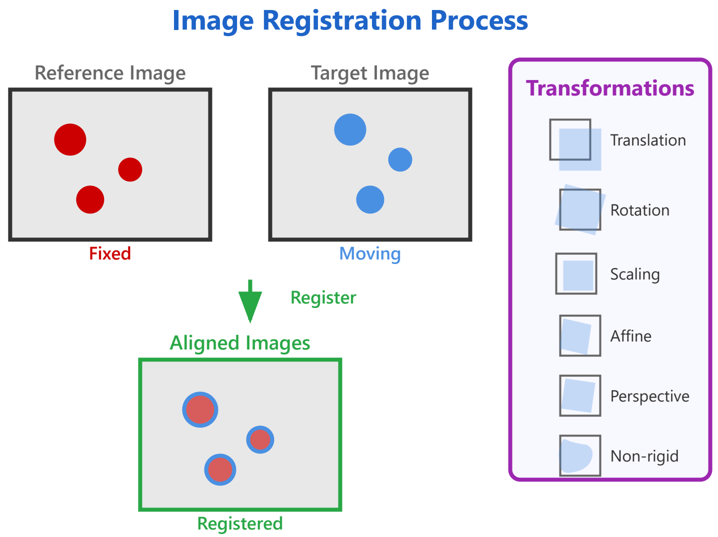
Fingerprint analysis, text recognition and OCR, medical image segmentation, defect detection in manufacturing, object counting, boundary extraction, noise reduction in binary images, and shape analysis in computer vision systems.

# 5. Image Registration Basics

Image registration is the process of geometrically aligning two or more images of the same scene taken at different times, from different viewpoints, or by different sensors. The goal is to establish spatial correspondence between images so that they can be analyzed, compared, or integrated.

### Registration Components:

- **Feature Detection:** Identifying distinctive points or regions
- **Feature Matching:** Establishing correspondences between features
- **Transform Estimation:** Computing the geometric transformation
- **Image Resampling:** Applying transformation to align images




## Registration Methods

**Feature-Based Registration:** Identifies distinctive features (corners, edges, blobs) in both images, matches corresponding features, and estimates the transformation. Common algorithms include SIFT (Scale-Invariant Feature Transform), SURF (Speeded Up Robust Features), and ORB (Oriented FAST and Rotated BRIEF).

**Intensity-Based Registration:** Directly uses pixel intensity values without extracting explicit features. Optimizes a similarity metric (like mutual information or correlation) between the images. More robust for images without distinctive features but computationally intensive.

### Transformation Types:

- **Rigid:** Translation + rotation (preserves distances and angles) - 3 DOF
- **Similarity:** Rigid + uniform scaling - 4 DOF
- **Affine:** Similarity + shearing (preserves parallel lines) - 6 DOF
- **Perspective:** Projects 3D world onto 2D plane - 8 DOF
- **Non-rigid:** Local deformations, most complex - many DOF

**Similarity Metrics:** The quality of registration is evaluated using metrics like Sum of Squared Differences (SSD), Normalized Cross-Correlation (NCC), Mutual Information (MI), or Mean Squared Error (MSE). These metrics quantify how well the registered images align.

### Practical Applications:

Medical imaging (aligning CT and MRI scans), panoramic image stitching, change detection in satellite imagery, motion tracking and video stabilization, multi-modal image fusion, template matching, augmented reality, and autonomous vehicle navigation.

### Challenges in Registration:

- Handling different imaging modalities with different intensity characteristics
- Dealing with occlusions and missing data
- Computational complexity for high-resolution images
- Selecting appropriate transformation models
- Achieving sub-pixel accuracy when required