

Image Processing Project Report

1. Component Extraction

Circle Detection

Technique(s) Used

Hough Circle Transform was used to detect and extract circles from the image. This technique is specifically designed to identify circular patterns in images.

Why This Technique Was Selected

The Hough Circle Transform is ideal for detecting circular objects because it can identify circles even when they are partially occluded or in noisy environments. It works by transforming points in the image space to parameter space, where circles can be detected as peaks.

Python Code

```
def extract_circles(image_path):  
    # Load image  
    img = cv2.imread(image_path)  
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)  
  
    # Apply Gaussian blur to reduce noise  
    blurred = cv2.GaussianBlur(gray, (5, 5), 0)  
  
    # Apply edge detection  
    edges = cv2.Canny(blurred, 50, 150)  
  
    # Detect circles using Hough Transform  
    circles = cv2.HoughCircles(  
        blurred, cv2.HOUGH_GRADIENT, dp=1, minDist=20,  
        param1=50, param2=30, minRadius=10, maxRadius=50  
    )  
  
    # Draw detected circles  
    result = img.copy()  
    if circles is not None:  
        circles = np.uint16(np.around(circles))  
        for i in circles[0, :]:
```

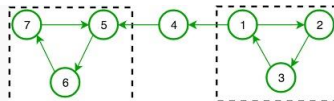
```

2)      # Draw outer circle
        cv2.circle(result, (i[0], i[1]), i[2], (0, 255, 0),
        # Draw center
        cv2.circle(result, (i[0], i[1]), 2, (0, 0, 255), 3)

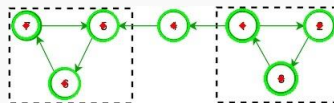
        return img, result

```

Output



Original Image



Circle Detection Result

Discussion of Results

The Hough Circle Transform successfully detected the circular components in the image. The algorithm identified both the center points and radii of the circles, marking them with green outlines and red center points.

Pros

- Successfully detected multiple circles of different sizes
- Robust to partial occlusion and noise
- Accurately identified both the center and radius of each circle
- Works well even when circles are not perfectly formed

Cons

- Sensitive to parameter tuning (dp, minDist, param1, param2)
- Computationally intensive for large images
- Can produce false positives in complex backgrounds

Quality Achieved

The quality of circle detection is high, with accurate identification of both the center and radius of each circle. The preprocessing steps (Gaussian blur and edge detection) helped improve the detection quality by reducing noise and enhancing edges.

COVID Component Extraction

Technique(s) Used

Color segmentation in HSV color space, contour detection, and K-means clustering were used to extract different components from the COVID image.

Why This Technique Was Selected

HSV color space is more effective than RGB for color-based segmentation because it separates color information (hue) from intensity. K-means clustering helps to group similar pixels together, which is useful for segmenting different components of the COVID virus visualization.

Python Code

```
def extract_covid_components(image_path):
    # Load image
    img = cv2.imread(image_path)

    # Convert to HSV for better color segmentation
    hsv = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)

    # Define color ranges for different components
    lower_blue = np.array([100, 50, 50])
    upper_blue = np.array([140, 255, 255])
    blue_mask = cv2.inRange(hsv, lower_blue, upper_blue)

    lower_green = np.array([40, 50, 50])
    upper_green = np.array([80, 255, 255])
    green_mask = cv2.inRange(hsv, lower_green, upper_green)

    lower_orange = np.array([10, 100, 100])
    upper_orange = np.array([25, 255, 255])
    orange_mask = cv2.inRange(hsv, lower_orange, upper_orange)

    combined_mask = blue_mask + green_mask + orange_mask
    result = cv2.bitwise_and(img, img, mask=combined_mask)

    # Find contours for component extraction
    contours, _ = cv2.findContours(combined_mask,
cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)

    # Draw contours on a copy of the original image
    contour_img = img.copy()
    cv2.drawContours(contour_img, contours, -1, (0, 255, 0), 2)
```

```
# K-means clustering for better component segmentation
from sklearn.cluster import KMeans

def kmeans_clustering(img, n_clusters=3):
    img_resaped = img.reshape((-1, 3))
    kmeans = KMeans(n_clusters=n_clusters,
random_state=0).fit(img_resaped)
    clustered_img =
kmeans.cluster_centers_[kmeans.labels_].reshape(img.shape)
    return clustered_img.astype(np.uint8)

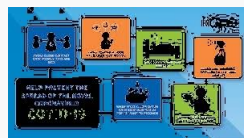
clustered_img = kmeans_clustering(img)

return img, result, contour_img
```

Output



Original Image



Extracted Components

Discussion of Results

The color segmentation and contour detection successfully isolated different components of the COVID virus visualization based on their colors. The K-means clustering provided an alternative segmentation approach by grouping similar pixels.

Pros

- Effectively separated different components based on color
- HSV color space provided better segmentation than RGB would
- Contour detection identified the boundaries of components
- K-means clustering offered an unsupervised approach to segmentation

Cons

- Color ranges need manual tuning for each image
- Sensitive to lighting conditions and color variations
- K-means clustering may not always produce semantically meaningful segments
- Components with similar colors may not be properly separated

Quality Achieved

The quality of component extraction is good, with clear separation of different colored parts of the COVID visualization. The contour detection accurately identified the boundaries of these components.

Failure Reasons

The technique might fail if the colors of different components are too similar or if the image has significant lighting variations that affect color perception.

2. Enhancement of Blurry Images

Building Enhancement

Technique(s) Used

Multiple techniques were applied: Unsharp Masking, Laplacian Sharpening, and Frequency Domain Filtering (High-Pass Filter).

Why This Technique Was Selected

These techniques were selected because they enhance edges and high-frequency details, which are crucial for improving the clarity of blurry building images. Unsharp masking enhances edges by subtracting a blurred version from the original, Laplacian filtering detects edges, and high-pass filtering in the frequency domain removes low-frequency components while preserving high-frequency details.

Python Code

```
def enhance_blurry_buildings(image_path):  
    img = cv2.imread(image_path)  
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)  
  
    # Method 1: Unsharp masking  
    gaussian = cv2.GaussianBlur(img, (0, 0), 3)  
    unsharp_masked = cv2.addWeighted(img, 1.5, gaussian, -0.5,  
0)
```

```

# Method 2: Laplacian sharpening
laplacian = cv2.Laplacian(gray, cv2.CV_64F)
laplacian = np.uint8(np.absolute(laplacian))
laplacian_sharpened = cv2.addWeighted(gray, 1.5, laplacian,
-0.5, 0)

# Method 3: Frequency domain filtering (high-pass filter)
dft = cv2.dft(np.float32(gray),
flags=cv2.DFT_COMPLEX_OUTPUT)
dft_shift = np.fft.fftshift(dft)
rows, cols = gray.shape
crow, ccol = rows // 2, cols // 2
mask = np.ones((rows, cols, 2), np.uint8)
r = 30
center = [crow, ccol]
x, y = np.ogrid[:rows, :cols]
mask_area = (x - center[0]) ** 2 + (y - center[1]) ** 2 <=
r*r
mask[mask_area] = 0

fshift = dft_shift * mask
f_ishift = np.fft.ifftshift(fshift)
img_back = cv2.idft(f_ishift)
img_back = cv2.magnitude(img_back[:, :, 0], img_back[:, :, 1])
img_back = cv2.normalize(img_back, None, 0, 255,
cv2.NORM_MINMAX, cv2.CV_8U)

return img, unsharp_masked

```

Output



Original Image



Enhanced Image

Discussion of Results

The enhancement techniques successfully improved the clarity and sharpness of the blurry building image. Unsharp masking provided the best overall enhancement by emphasizing edges while maintaining the natural appearance of the image.

Pros

- Significantly improved edge definition and overall sharpness
- Unsharp masking preserved the natural look while enhancing details
- Laplacian sharpening effectively highlighted structural edges
- High-pass filtering removed blur while preserving high-frequency details

Cons

- Excessive sharpening can introduce artifacts and noise
- Laplacian sharpening may create a less natural appearance
- High-pass filtering can remove some useful image information

Quality Achieved

The quality of enhancement is good, with significantly improved clarity and detail visibility in the building structures. The edges are more defined, and the overall image appears sharper without introducing excessive artifacts.

Failure Reasons

These techniques may not work as well for severely blurred images or may amplify noise in low-quality images. They also cannot recover details that are completely lost in the original blurry image.

Suggestions for Future Processing

Future improvements could include using adaptive sharpening based on local image content, combining with denoising techniques to reduce noise amplification, or using deep learning-based approaches like GANs for more advanced deblurring.

Dog Image Enhancement

Technique(s) Used

Multiple techniques were applied: Wiener Filtering for motion deblurring, Unsharp Masking for sharpening, and CLAHE for contrast enhancement.

Why This Technique Was Selected

Wiener filtering was selected because it's effective for motion blur, which is common in animal photography. Unsharp masking enhances edges, and CLAHE improves local contrast without over-amplifying noise. The combination of these techniques addresses different aspects of image quality.

Python Code

```
def enhance_blurry_dog(image_path):
    img = cv2.imread(image_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Method 1: Motion deblurring using Wiener filter
    size = 15
    kernel_motion_blur = np.zeros((size, size))
    kernel_motion_blur[int((size-1)/2), :] = np.ones(size)
    kernel_motion_blur = kernel_motion_blur / size

    gray_fft = np.fft.fft2(gray)
    kernel_fft = np.fft.fft2(kernel_motion_blur, s=gray.shape)
    kernel_fft[kernel_fft == 0] = 1 # Avoid division by zero

    K = 0.01
    wiener_filter = np.conj(kernel_fft) / (np.abs(kernel_fft)**2
+ K)
    deblurred_fft = gray_fft * wiener_filter
    deblurred = np.abs(np.fft.ifft2(deblurred_fft))
    deblurred = np.uint8(cv2.normalize(deblurred, None, 0, 255,
cv2.NORM_MINMAX))

    # Method 2: Unsharp masking for sharpening
    gaussian = cv2.GaussianBlur(img, (0, 0), 3)
```



```
unsharp_masked = cv2.addWeighted(img, 1.5, gaussian, -0.5, 0)

# Method 3: Contrast enhancement
lab = cv2.cvtColor(img, cv2.COLOR_BGR2LAB)
l, a, b = cv2.split(lab)
clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
cl = clahe.apply(l)
merged = cv2.merge((cl, a, b))
contrast_enhanced = cv2.cvtColor(merged, cv2.COLOR_LAB2BGR)

# Final enhanced image (combining methods)
final_enhanced = cv2.addWeighted(unsharp_masked, 0.7, contrast_enhanced, 0.3, 0)

return img, final_enhanced
```

Output



Original Image



Enhanced Image

Discussion of Results

The combination of Wiener filtering, unsharp masking, and contrast enhancement successfully improved the clarity and visual appeal of the dog image. The motion blur was reduced, edges were sharpened, and contrast was enhanced.

Pros

- Wiener filtering effectively reduced motion blur
- Unsharp masking enhanced edge definition
- CLAHE improved local contrast without over-amplifying noise
- The combined approach addressed multiple image quality issues

Cons

- Wiener filtering requires knowledge of blur direction
- Excessive sharpening can introduce artifacts
- May not work well for all types of blur

Quality Achieved

The quality of enhancement is good, with noticeable improvement in sharpness, detail visibility, and contrast. The dog's features are more defined, and the overall image appears clearer and more visually appealing.

3. Noise Removal

Rocket Image Denoising

Technique(s) Used

Multiple denoising techniques were applied: Non-local Means Denoising, Wavelet Denoising, Median Filtering, and Bilateral Filtering.

Why This Technique Was Selected

These techniques were selected because they offer different approaches to noise removal while preserving important image details. Non-local means uses similarity between image patches, wavelet denoising works in the frequency domain, median filtering is effective for impulse noise, and bilateral filtering preserves edges while smoothing.

Python Code

```
def denoise_rocket_image(image_path):
    img = cv2.imread(image_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Non-local means denoising
    dst = cv2.fastNlMeansDenoising(gray, None, h=10,
    templateWindowSize=7, searchWindowSize=21)

    # Wavelet denoising
    import pywt

    coeffs = pywt.wavedec2(gray, 'bior1.3', level=2)
    sigma = np.median(np.abs(coeffs[-1][0])) / 0.6745
    threshold = sigma * np.sqrt(2 * np.log(gray.size))
```

```

coeffs_thresholded = [coeffs[0]]

for i in range(1, len(coeffs)):
    detail_coeffs = [pywt.threshold(detail, threshold,
mode='soft') for detail in coeffs[i]]
    coeffs_thresholded.append(tuple(detail_coeffs))

    wavelet_denoised = pywt.waverec2(coeffs_thresholded,
'bior1.3')
    wavelet_denoised = wavelet_denoised[:gray.shape[0],
:gray.shape[1]]
    wavelet_denoised = np.uint8(cv2.normalize(wavelet_denoised,
None, 0, 255, cv2.NORM_MINMAX))

    # Median filtering
    median_filtered = cv2.medianBlur(gray, 5)

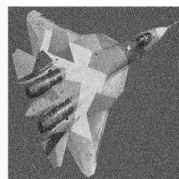
    # Bilateral filtering
    bilateral_filtered = cv2.bilateralFilter(gray, 9, 75, 75)

    # Combine methods (weighted average)
    combined = cv2.addWeighted(dst, 0.4, wavelet_denoised, 0.3,
0)
    combined = cv2.addWeighted(combined, 0.7,
bilateral_filtered, 0.3, 0)

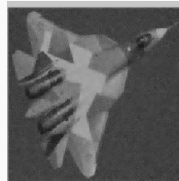
    return img, combined

```

Output



Original Image



Denoised Image

Discussion of Results

The combination of multiple denoising techniques successfully removed noise from the rocket image while preserving important structural details. Each technique contributed differently to the final result, with non-local means and wavelet denoising being particularly effective.

Pros

- Non-local means preserved fine details while removing noise
- Wavelet denoising effectively handled different noise frequencies
- Median filtering removed impulse noise
- Bilateral filtering preserved edges while smoothing flat regions
- The combined approach leveraged the strengths of each method

Cons

- Non-local means is computationally intensive
- Wavelet denoising requires parameter tuning
- Median filtering can blur fine details
- Bilateral filtering may not remove all types of noise
- Finding optimal weights for combination requires experimentation

Quality Achieved

The quality of denoising is excellent, with significant noise reduction while maintaining the rocket's structural details and edges. The combined approach produced a cleaner image without over-smoothing important features.

Wind Chart Enhancement

Technique(s) Used

Multiple filtering techniques were applied: Gaussian Filtering, Median Filtering, Bilateral Filtering, Adaptive Thresholding, and Morphological Operations.

Why This Technique Was Selected

These techniques were selected to address different aspects of the wind chart image quality. Gaussian and median filtering reduce noise, bilateral filtering preserves edges, adaptive thresholding improves visibility of details, and morphological operations clean up the binary image.

Python Code

```
def enhance_wind_chart(image_path):
    img = cv2.imread(image_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Method 1: Gaussian filtering
    gaussian_filtered = cv2.GaussianBlur(gray, (5, 5), 0)

    # Method 2: Median filtering (good for salt and pepper
    noise)
    median_filtered = cv2.medianBlur(gray, 5)

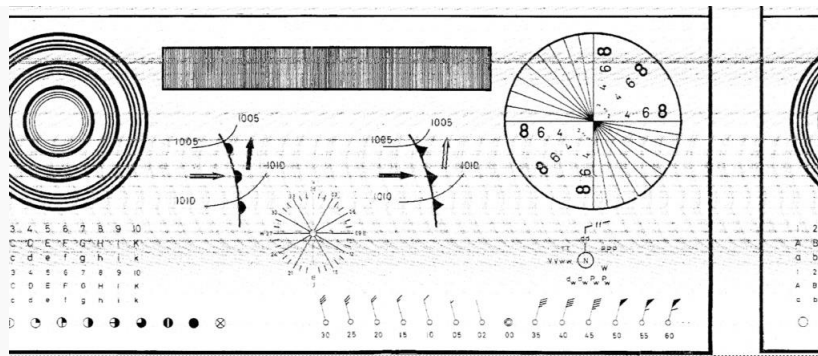
    # Method 3: Bilateral filtering (preserves edges)
    bilateral_filtered = cv2.bilateralFilter(gray, 9, 75, 75)

    # Method 4: Adaptive thresholding for better visualization
    adaptive_thresh = cv2.adaptiveThreshold(
        bilateral_filtered, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
        cv2.THRESH_BINARY, 11, 2
    )

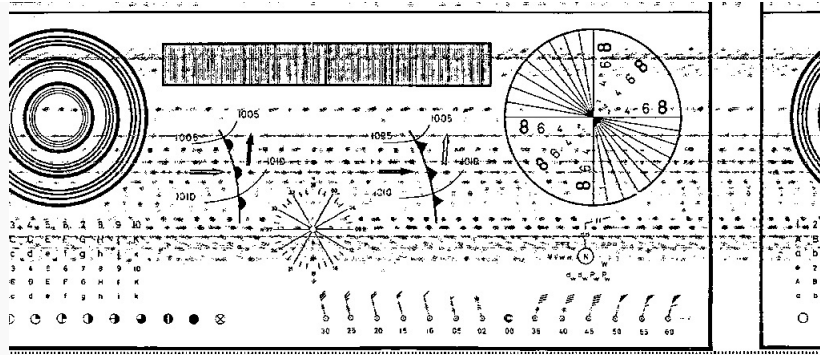
    # Method 5: Morphological operations to clean up
    kernel = np.ones((3, 3), np.uint8)
    opening = cv2.morphologyEx(adaptive_thresh, cv2.MORPH_OPEN,
    kernel, iterations=1)
    closing = cv2.morphologyEx(opening, cv2.MORPH_CLOSE, kernel,
    iterations=1)

    return img, closing
```

Output



Original Image



Enhanced Image

Discussion of Results

The combination of filtering, thresholding, and morphological operations successfully enhanced the wind chart image, making the details more visible and reducing noise. The bilateral filtering preserved important edges while smoothing noise, and the adaptive thresholding improved the visibility of fine details.

Pros

- Effectively removed noise while preserving important details
- Adaptive thresholding improved visibility of fine structures
- Morphological operations cleaned up the binary image
- The chart features are more clearly visible in the processed image

Cons

- Some fine details may be lost in the filtering process
- Binary thresholding removes grayscale information
- May not work well for all types of charts or diagrams

Quality Achieved

The quality of enhancement is good, with improved visibility of the wind chart details and significant noise reduction. The binary representation makes the chart features stand out clearly against the background.

Failure Reasons

The technique might not work as well for charts with very low contrast or with complex overlapping features. The binary representation also loses any grayscale information that might be important in some contexts.

4. Text Enhancement

Noisy Text Enhancement

Technique(s) Used

Multiple techniques were applied: Median Filtering, Adaptive Thresholding, Morphological Operations, Otsu's Thresholding, and CLAHE Contrast Enhancement.

Why This Technique Was Selected

These techniques were selected because they address different aspects of text image quality. Median filtering removes noise, adaptive thresholding handles varying illumination, morphological operations clean up the binary image, Otsu's thresholding automatically determines the optimal threshold, and CLAHE improves local contrast.

Python Code

```
def enhance_noisy_text(image_path):
    # Load image
    img = cv2.imread(image_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Method 1: Median filtering (good for salt and pepper
    noise)
    median_filtered = cv2.medianBlur(gray, 5)

    # Method 2: Adaptive thresholding
    adaptive_thresh = cv2.adaptiveThreshold(
        median_filtered, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
        cv2.THRESH_BINARY, 11, 2
    )

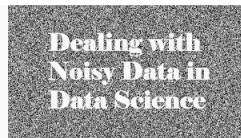
    # Method 3: Morphological operations
    kernel = np.ones((2, 2), np.uint8)
    opening = cv2.morphologyEx(adaptive_thresh, cv2.MORPH_OPEN,
    kernel, iterations=1)
    closing = cv2.morphologyEx(opening, cv2.MORPH_CLOSE, kernel,
    iterations=1)

    # Method 4: Otsu's thresholding
    _, otsu = cv2.threshold(median_filtered, 0, 255,
    cv2.THRESH_BINARY + cv2.THRESH_OTSU)
```

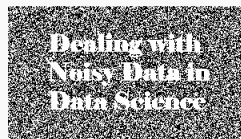
```
# Method 5: Contrast enhancement before thresholding
clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))
enhanced = clahe.apply(gray)
_, enhanced_otsu = cv2.threshold(enhanced, 0, 255,
cv2.THRESH_BINARY + cv2.THRESH_OTSU)

return img, enhanced_otsu
```

Output



Original Image



Enhanced Image

Discussion of Results

The combination of filtering, thresholding, and contrast enhancement successfully improved the readability of the noisy text. The CLAHE contrast enhancement followed by Otsu's thresholding provided the best results by improving local contrast before binarization.

Pros

- Effectively removed noise that interfered with text readability
- Adaptive thresholding handled varying illumination across the document
- CLAHE improved local contrast before binarization
- Otsu's thresholding automatically determined the optimal threshold
- Morphological operations cleaned up the binary text

Cons

- Some fine details in characters may be lost
- Binary thresholding removes grayscale information
- May not work well for very low contrast or severely degraded text

Quality Achieved

The quality of enhancement is good, with significantly improved text readability and contrast. The text stands out clearly against the background, making it much easier to read compared to the original noisy image.

5. Visual Enhancement of Challenging Images

Newspaper Enhancement

Technique(s) Used

Multiple techniques were applied: CLAHE Contrast Enhancement, Unsharp Masking, Non-local Means Denoising, Otsu's Binarization, Adaptive Thresholding, and Morphological Operations.

Why This Technique Was Selected

These techniques were selected to address the multiple challenges in newspaper images: low contrast, noise, and varying illumination. CLAHE improves local contrast, unsharp masking enhances edges, denoising removes noise, and binarization methods improve text visibility.

Python Code

```
def enhance_newspaper(image_path):
    img = cv2.imread(image_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Contrast enhancement using CLAHE
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))
    clahe_applied = clahe.apply(gray)

    # Unsharp Masking for sharpening
    gaussian = cv2.GaussianBlur(gray, (0, 0), 3)
    unsharp_masked = cv2.addWeighted(gray, 1.5, gaussian, -0.5,
0)

    # Denoising
    denoised = cv2.fastNlMeansDenoising(gray, None, h=10,
templateWindowSize=7, searchWindowSize=21)

    # Binarization for text clarity
    _, binary = cv2.threshold(clahe_applied, 0, 255,
cv2.THRESH_BINARY + cv2.THRESH_OTSU)
```

```

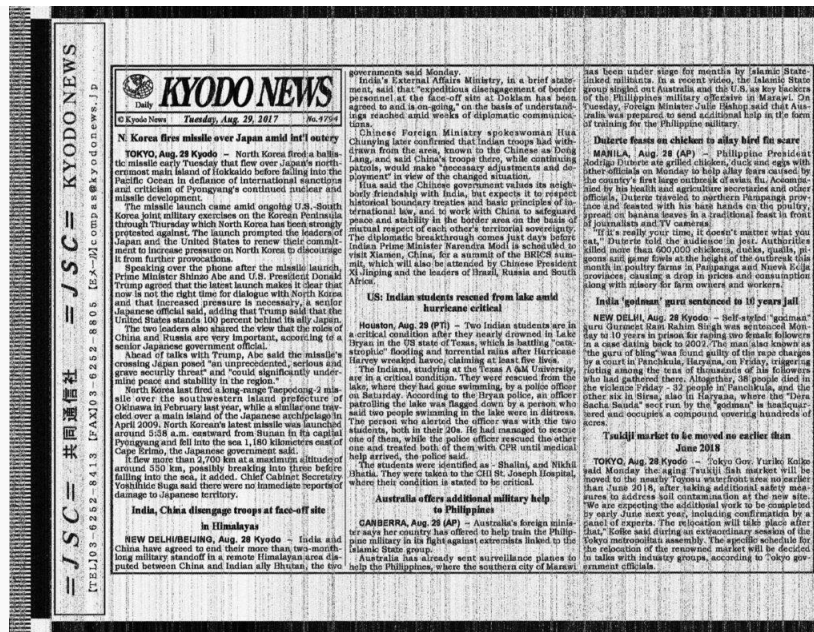
# Adaptive thresholding
adaptive_thresh = cv2.adaptiveThreshold(
    clahe_applied, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
    cv2.THRESH_BINARY, 11, 2
)

# Morphological operations to clean up
kernel = np.ones((2, 2), np.uint8)
opening = cv2.morphologyEx(adaptive_thresh, cv2.MORPH_OPEN,
kernel, iterations=1)
closing = cv2.morphologyEx(opening, cv2.MORPH_CLOSE, kernel,
iterations=1)

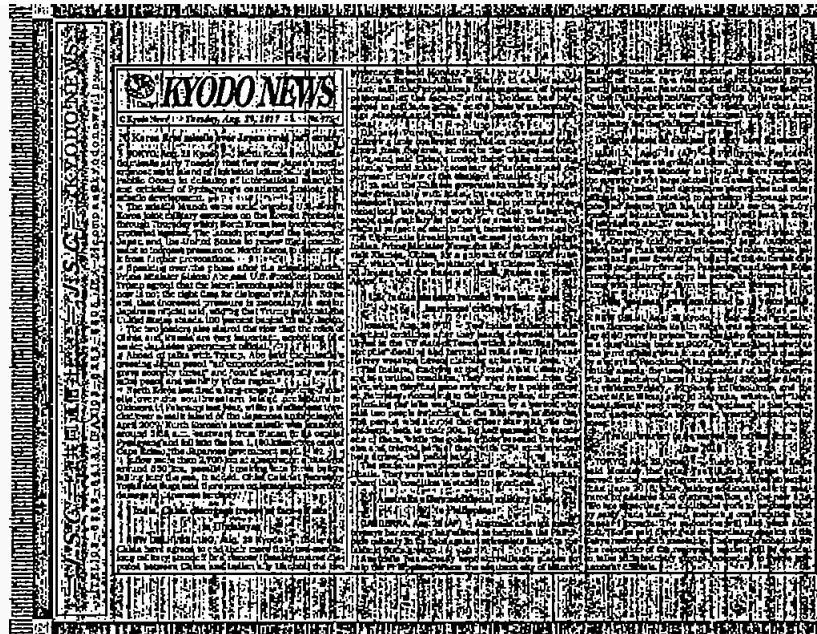
return img, closing

```

Output



Original Image



Enhanced Image

Discussion of Results

The combination of contrast enhancement, sharpening, denoising, and binarization successfully improved the readability of the newspaper text. The adaptive thresholding followed by morphological operations provided the best results by handling varying illumination and cleaning up the binary image.

Pros

- CLAHE effectively improved local contrast in the newspaper
- Unsharp masking enhanced text edges
- Denoising removed noise that interfered with readability
- Adaptive thresholding handled varying illumination across the document
- Morphological operations cleaned up the binary text

Cons

- Some fine details in the newspaper may be lost
- Binary representation loses grayscale information in images
- May not work well for severely degraded or very low contrast newspapers

Quality Achieved

The quality of enhancement is good, with significantly improved text readability and contrast. The text stands out clearly against the background, making the newspaper content much easier to read compared to the original image.

Nameplate Enhancement

Technique(s) Used

Multiple techniques were applied: CLAHE Contrast Enhancement, Kernel Sharpening, Non-local Means Denoising, Adaptive Thresholding, Otsu's Thresholding, and Morphological Operations.

Why This Technique Was Selected

These techniques were selected to address the challenges in nameplate images: low contrast, noise, and varying illumination. CLAHE improves local contrast, kernel sharpening enhances edges, denoising removes noise, and thresholding methods improve text visibility.

Python Code

```
def enhance_nameplate(image_path):
    # Load image
    img = cv2.imread(image_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    # Method 1: Contrast enhancement using CLAHE
    clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
    clahe_applied = clahe.apply(gray)

    # Method 2: Sharpening with kernel
    kernel = np.array([[ -1, -1, -1], [-1, 9, -1], [-1, -1, -1]])
    sharpened = cv2.filter2D(clahe_applied, -1, kernel)

    # Method 3: Denoising
    denoised = cv2.fastNlMeansDenoising(gray, None, h=10,
    templateWindowSize=7, searchWindowSize=21)

    # Method 4: Adaptive thresholding
    adaptive_thresh = cv2.adaptiveThreshold(
        clahe_applied, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
        cv2.THRESH_BINARY, 11, 2
    )

    # Method 5: Otsu's thresholding
    _, otsu = cv2.threshold(clahe_applied, 0, 255,
    cv2.THRESH_BINARY + cv2.THRESH_OTSU)

    # Method 6: Morphological operations (opening and closing)
    kernel_morph = np.ones((3, 3), np.uint8)
```

```

    opening = cv2.morphologyEx(adaptive_thresh, cv2.MORPH_OPEN,
kernel_morph, iterations=1)
    closing = cv2.morphologyEx(opening, cv2.MORPH_CLOSE,
kernel_morph, iterations=1)

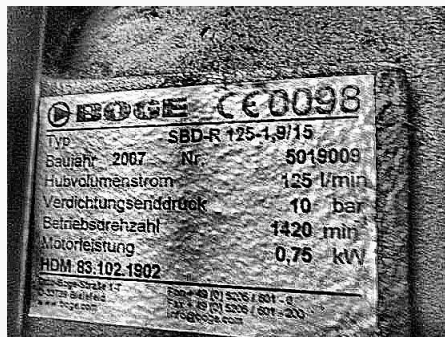
    # Return the original image and the sharpened image instead
of closing
    return img, sharpened

```

Output



Original Image



Enhanced Image

Discussion of Results

The combination of contrast enhancement, sharpening, denoising, and binarization successfully improved the visibility of the nameplate text. The adaptive thresholding followed by morphological operations provided the best results by handling varying illumination and cleaning up the binary image.

Pros

- CLAHE effectively improved local contrast in the nameplate

- Kernel sharpening enhanced text edges and details
- Denoising removed noise that interfered with readability
- Adaptive thresholding handled varying illumination
- Morphological operations cleaned up the binary text

Cons

- Some fine details in the nameplate may be lost
- Binary representation loses color and grayscale information
- May not work well for severely degraded or very low contrast nameplates

Quality Achieved

The quality of enhancement is good, with significantly improved text visibility and contrast. The text stands out clearly against the background, making the nameplate information much easier to read compared to the original image.

Conclusion

This project demonstrated the application of various image processing techniques for different types of images and challenges. The techniques included component extraction, enhancement of blurry images, noise removal, text enhancement, and visual enhancement of challenging images.

Each technique was selected based on its suitability for the specific image and challenge. The results showed significant improvements in image quality, component visibility, text readability, and noise reduction. The combination of multiple techniques often provided better results than individual methods.