Texture Analysis of Images in Spatial and Spectral Domain

Aniket Karkala - 21104A0020

Shubhang Mehta - 21104A0004

Guide: **Dr. Varsha Turkar**

HOD, Department of Electronics And Telecommunication Engineering

Vidyalankar Institute of Technology, Wadala(E), Mumbai

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Abstract

This report explores texture analysis in images, focusing on spatial and spectral domains. Texture is crucial in image processing and computer vision applications like classification, segmentation, synthesis, and shape recovery. The report introduces texture analysis methods and four research directions: classification, segmentation, synthesis, and shape recovery. It discusses spatial domain processing techniques like the Gray-Level Co-occurrence Matrix (GLCM) method and spectral domain methods like Fourier, Gabor, and Wavelet transforms. Results show texture analysis on grayscale images of a green apple and a sweet lime, and compare texture properties from GLCM matrices.

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0.1 What is Texture?

Texture is a fundamental property of surfaces that describes the visual patterns of their spatial variations. It is an important feature in many image processing and computer vision applications, such as image classification, segmentation, retrieval, and synthesis.

0.2 Introduction to Texture Analysis

Texture analysis refers to the characterization of regions in an image by their texture content. Texture analysis attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities. In this sense, the roughness or bumpiness refers to variations in the intensity values, or gray levels.
Texture analysis is used in various applications, including remote sensing, automated inspection, and medical image processing. Texture analysis can be used to find the texture boundaries, called texture segmentation. Texture analysis can be helpful when objects in an image are more characterized by their texture than by intensity, and traditional thresholding techniques cannot be used effectively.

0.2.1 Texture representation

There are two main methods for representing textures:

- **Statistical methods:** These methods represent textures using statistical features, such as the gray level co-occurrence matrix (GLCM). The GLCM is a two-dimensional histogram that shows the probability of co-occurrence of two pixels with specific intensity values. From the GLCM, several parameters can be extracted to describe a particular texture, such as contrast, homogeneity, uniformity, and entropy.

- **Spectral methods:** These methods represent textures using their frequency domain representation. The Fourier transform is a mathematical tool that converts an image from the spatial domain to the frequency domain. By analyzing the spectrum of the image, we can extract texture features like the principal direction of the texture pattern and the fundamental spatial period of the patterns.

0.2.2 Research directions in texture analysis

There are four main research directions in texture analysis as described in [2]:

- **Texture classification:** The first research direction in texture analysis is texture classification. This task aims to classify an image into a particular texture class, such as brick, grass, or wood. There are many different methods for texture classification, but some of the most common methods include:

  - **Statistical methods**: These methods use statistical features of the texture, such as the mean, standard deviation, and entropy, to classify the texture.
  - **Spectral methods:** These methods use the frequency domain representation of the texture to classify the texture.

- **Texture segmentation:** The second research direction in texture analysis is texture segmentation. This task aims to partition an image into regions with different textures. There are many different methods for texture segmentation, but some of the most common methods include:

  - **Thresholding methods**: These methods threshold the image based on the intensity values of the pixels.

- **Texture synthesis:** The third research direction in texture analysis is texture synthesis. This task aims to generate new textures that are like a given sample texture. There are many different methods for texture synthesis, but some of the common methods include:
  - **Statistical methods:** These methods generate new textures by sampling from a statistical model of the texture.
  - Spectral methods: These methods generate new textures by manipulating the frequency domain representation of the texture.
- **Shape from texture:** The fourth research direction in texture analysis is shape from texture. This task aims to recover the 3D shape of an object from its texture. There are many different methods for shape from texture, but some of the common methods include:
  - **Deformation methods:** These methods deform a template mesh to match the texture of the image.
  - **Photometric stereo methods:** These methods use the shading of the object to recover its shape.

0.3 Image Texture Processing in Spatial domain

Gray-Level Co-occurrence Matrix (GLCM) technique: The Gray-Level Co-occurrence Matrix (GLCM) is a popular method used in texture analysis to quantify the spatial relationship between pixel intensities in an image. Essentially, it captures how often pairs of pixel values occur together at a certain spatial offset within an image. By analyzing these co-occurrence patterns, GLCM provides valuable insights into texture properties such as homogeneity, contrast, and directionality. As in [3], GLCM is a second order moment, thus considering relationship between two pixels. There are various in-built Matlab functions in [1] to carry out various operations using GLCM.
Once you have the GLCM, you can extract various features to describe the texture, such as:

- **Contrast:** A measure of the local variations in the image.
- **Entropy:** A measure of the randomness of the gray level distribution.
- **Homogeneity:** A measure of how similar the gray levels are in a local area.
- **Moment of inertia:** A measure of the distribution of gray level pairs around the diagonal of the GLCM.

0.4 Image Texture Processing in Spectral domain

Spectral methods are a powerful tool for analyzing and processing textures in images. They work by transforming the image from the spatial domain (pixel intensities) to the frequency domain (energy distribution across different frequencies). This transformation allows you to capture essential characteristics of the texture, such as its periodicity, orientation, and coarseness.

0.4.1 Methods

- **Fourier Transform:** This classic method decomposes the image into its fundamental frequencies, revealing the dominant patterns in the texture. However, it lacks directional information.
- **Gabor Transform:** This method uses Gabor filters, which are like band-pass filters tuned to specific frequencies and orientations. This allows you to analyze textures with specific periodicity and directionality.
- **Wavelet Transform:** This method decomposes the image into "wavelets", which are localized in both space and frequency. This enables multi-scale analysis, capturing textures with varying granularities.

0.4.2 Advantages

- **Efficient Representation:** Spectral features are often compact and efficient for representing textures.
- **Scale and rotation invariance:** : Some methods like Gabor transform can be made invariant to scale and rotation changes.
- **Interpretability:** The frequency components often have a clear physical meaning related to the texture properties.

0.5 Results

(a) GrayScale Image

(b) Standard Deviation Filtered Image

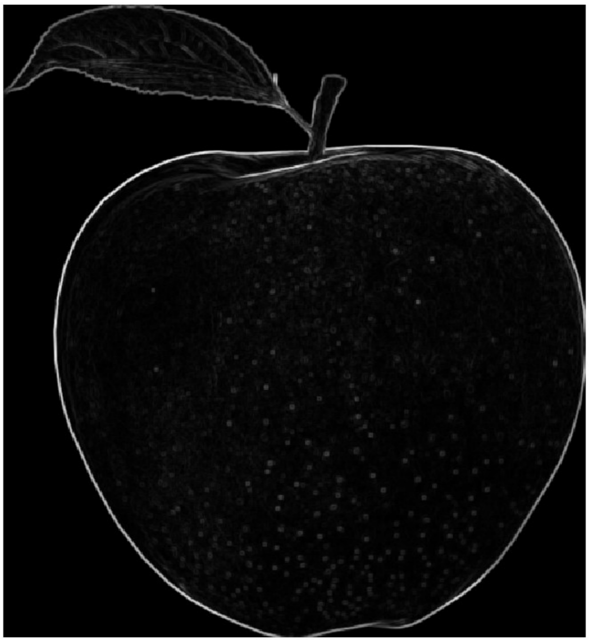

Figure 1: Figure 1a shows a grayscale image of a Green Apple. Figure 1b shows the standard deviation filtered image.
As we can observe, there are less variations on the surface of green apple which can be seen in Figure 1b highligted by the whitish spots. These variations are less since the texture of green apple in Figure 1a is relatively smooth. The homogenous areas have their intensities on the darker side as it is clearly visible in Figure 1b.

(a) GrayScale Image

(b) Standard Deviation Filtered Image

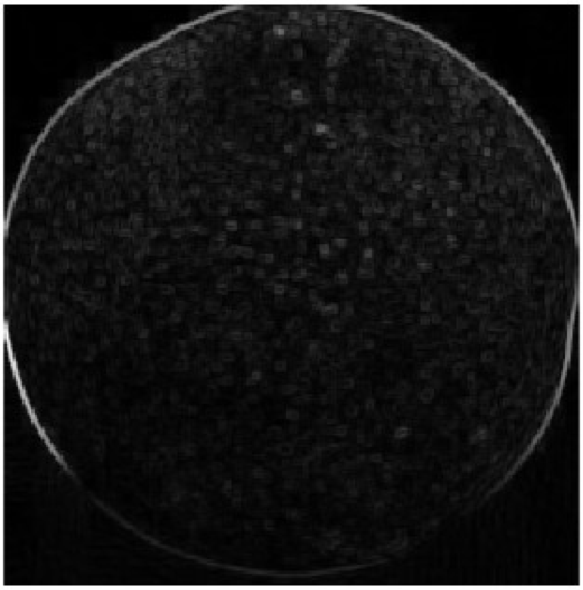

Figure 2: Figure 2a shows a grayscale image of a Sweet Lime. Figure 2b shows the standard deviation filtered image.
As we can observe, there are more variations on the surface of sweet lime which can be seen in Figure 2b highligted by the whitish spots. These variations are more since the texture of sweet lime in Figure 2a is relatively coarse/rough. The homogeneous areas have their intensities on the darker side as it is clearly visible in Figure 2b.

Offset	Sweetlime		Greenapple	
	Energy	Homogeneity	Energy	Homogeneity
1	0.0017	0.3926	0.1357	0.6142
2	0.0014	0.3429	0.1341	0.5807
3	0.0016	0.3940	0.1356	0.6189
4	0.014	0.3471	0.1341	0.5829

Table 1: Features extracted from GLCM

In Table 1, we have calculated the texture properties as Energy and Homogeneity using GLCM. It can be observed that the homogeneity and the energy in sweet lime is lesser than that of green apple. We have used the in-built Matlab functions in [1] to calculate the GLCM and extracted the required features.

0.6 References

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