What is an image?

An "image function" is a mapping from R^2 (that is, two real numbers representing a position (x, y) in the image) to R (that is some intensity or value). In the real world, images have a finite size or dimension, so thus we have:

I: $R^2 \rightarrow R$

More specifically,

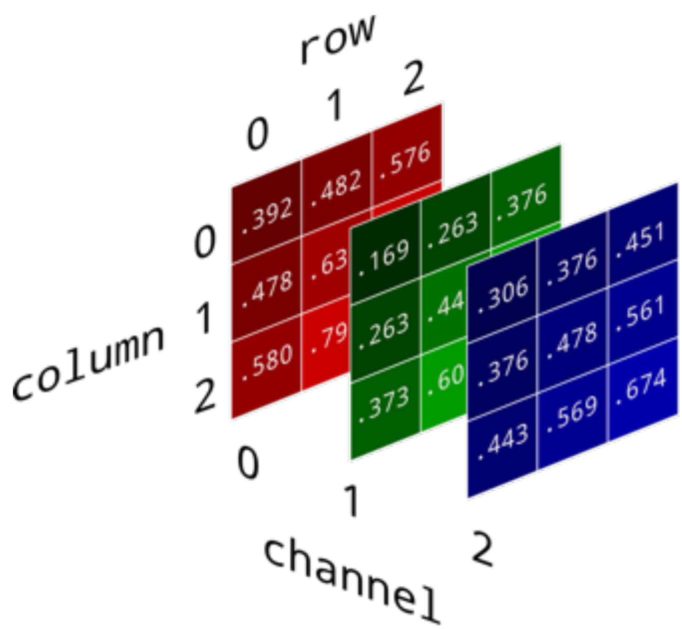
I: $x \times y \rightarrow R$ where $x \in [a, b]$, $y \in [c, d]$, and $R \in [min, max]$,

where min would be some "blackest black" and max would be some "whitest white," and (a, b, c, d) are ranges for the different dimensions of the images, though when actually performing mathematical operations, such interpretations of values become irrelevant.

We can easily expand this to color images, with a vector-valued function mapping each color component:

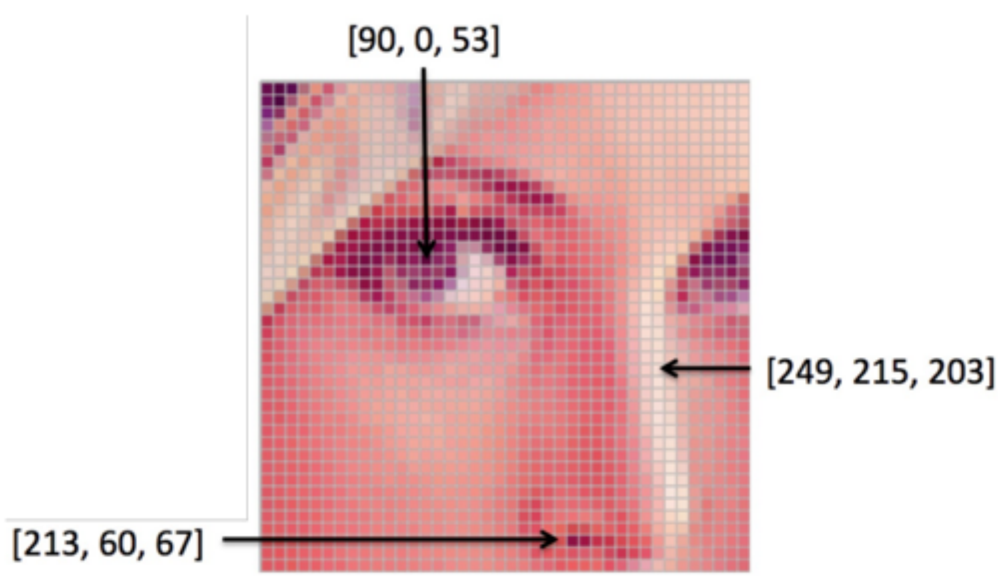
$$I(x, y) = \begin{bmatrix} r(x, y) \\ g(x, y) \\ b(x, y) \end{bmatrix}$$

(Fundamentals of Computer Vision, George Kudrayvtsev)



(https://e2eml.school/convert_rgb_to_grayscale.html)

Each pixel consists of three, instead of one, values. These three values correspond to the three primary colors: Red, Green, Blue.



(https://www.chegg.com/homework-help/questions-and-answers/background-digital-image-dimensions-h-times-w-represented-matrix-pixels-h-rows-w-columns-g-q102348031)

Pixel Intensity: The numerical value assigned to each pixel, which corresponds to the brightness or color of the pixel. For grayscale images, the intensity values range from 0 (black) to 255 (white), while for color images, the intensity values are typically represented using three color channels (red, green, and blue) and range from 0 to 255 for each channel. The formula for calculating the intensity of a pixel at location (x, y) in a grayscale image I is given by:

$I(x, y) = I_{gray}(x, y)$

where $I_{gray}(x, y)$ is the grayscale intensity value at location (x, y).

Image Resolution: The number of pixels in an image, typically measured in terms of width and height. The total number of pixels in an image is given by the product of the width and height. The formula for calculating the total number of pixels in an image of width W and height H is:

$N = W \times H$

Color Depth: The number of bits used to represent each pixel, which determines the number of colors that can be displayed in the image. For grayscale images, the color depth is typically 8 bits (or 1 byte), which allows for 256 different intensity values. For color images, the color depth is typically 24 bits (or 3 bytes), with 8 bits per color channel, which allows for $256^3 = 16,777,216$ different color combinations. The formula for calculating the color depth in bits is:

$D = B \times C$

where B is the number of bytes per pixel and C is the number of channels.

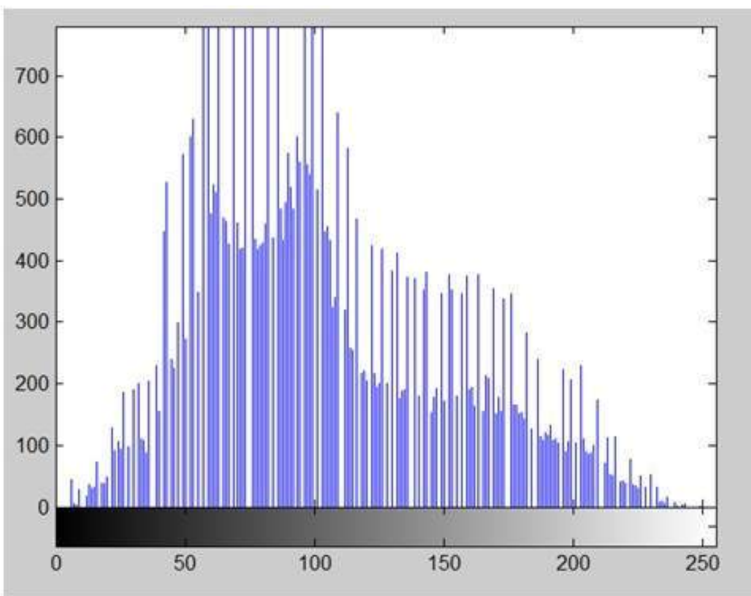
Image Enhancement Techniques

Image enhancement techniques are used to improve the visual quality and clarity of digital images by adjusting the brightness, contrast, color, and sharpness of the image. Enhancement techniques are typically applied to correct image imperfections such as noise, blurring, low contrast, and artifacts caused by compression.

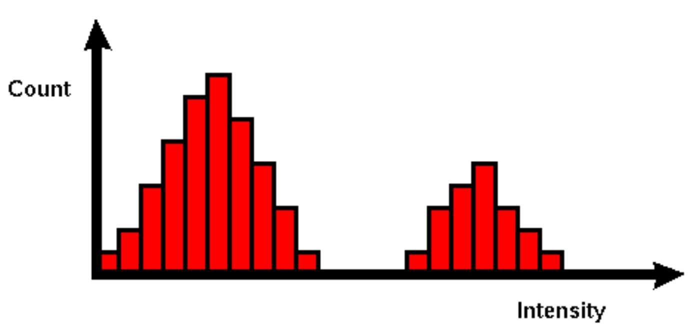
1- Histogram Equalization

A histogram is a graphical representation of the frequency distribution of a set of data. In the context of digital image processing, a histogram is a graph that shows the distribution of pixel intensities in an image. The x-axis of the histogram represents the possible values of pixel intensity (ranging from 0 to 255 for an 8-bit grayscale image), and the y-axis represents the number of pixels in the image with that intensity value.

A histogram provides valuable information about the distribution of pixel intensities in an image, which can be used to analyze and process the image in various ways. For example, a histogram can reveal the overall brightness and contrast of the image, as well as the presence of shadows, highlights, and other features. Histogram analysis can be used to adjust the brightness and contrast of an image, to detect and correct image imperfections such as noise and artifacts, and to perform feature extraction and image segmentation tasks.



(https://www.tutorialspoint.com/dip/histograms_introduction.htm)



(https://homepages.inf.ed.ac.uk/rbf/HIPR2/histgram.htm)

Histogram equalization is a popular image enhancement technique used to improve the contrast and brightness of digital images. The technique works by redistributing the pixel intensities in an image to produce a more uniform histogram, which results in an image with improved contrast and visibility of details.

The histogram equalization algorithm involves several steps. First, the image histogram is computed, which is a graph of the frequency distribution of pixel intensities in the image. The histogram is typically represented as a vector h(k), where k represents the intensity level (ranging from 0 to 255 for an 8-bit grayscale image) and h(k) represents the number of pixels in the image with intensity level k. The histogram equalization algorithm then computes a cumulative distribution function (CDF) of the pixel intensities, which is a mapping function that transforms the original pixel intensities to new values that span the full range of intensity values. The CDF is defined as:

$$\text{CDF}(k) = \sum_{j=0}^{k} \frac{h(j)}{N}$$

where N is the total number of pixels in the image, and the summation is performed over all intensity levels from 0 to k.

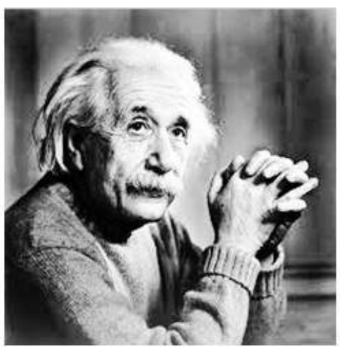
Once the CDF is computed, the pixel intensities in the image are transformed using the following mapping function:

s = T(r) = round((L-1) * CDF(r))

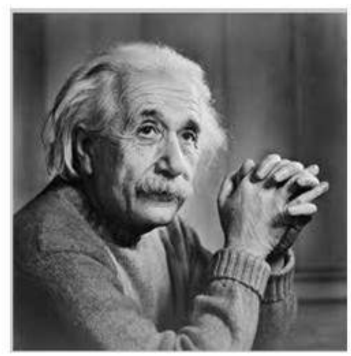
where s is the new pixel intensity value, r is the original pixel intensity value, L is the maximum intensity value (i.e., 256 for an 8-bit grayscale image), and round() rounds the result to the nearest integer. The transformed image has a more uniform histogram, which results in improved contrast and visibility of details.

Histogram equalization is a simple and effective technique for improving the visual quality of digital images, but it has some limitations. In particular, it may produce artifacts such as over-enhancement and noise amplification in regions of the image with low contrast or high noise levels. To address these limitations, several variations and extensions of histogram equalization have been proposed, such as adaptive histogram equalization and contrast-limited adaptive histogram equalization.

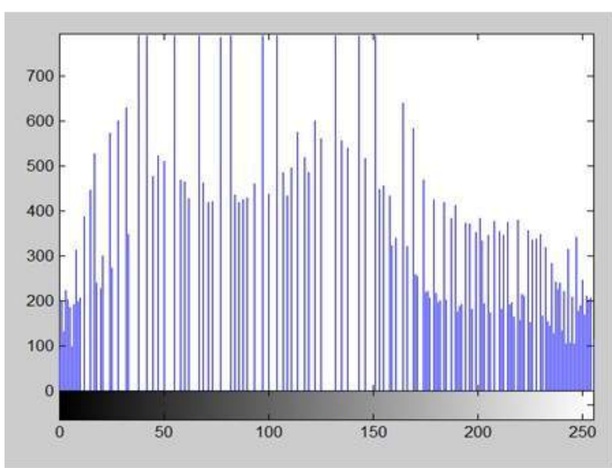
New Image



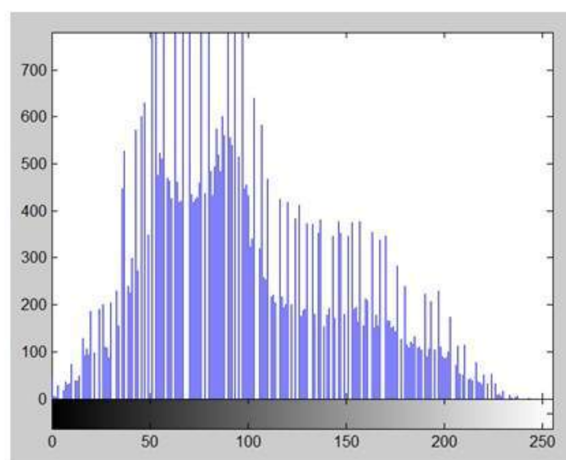
Old image



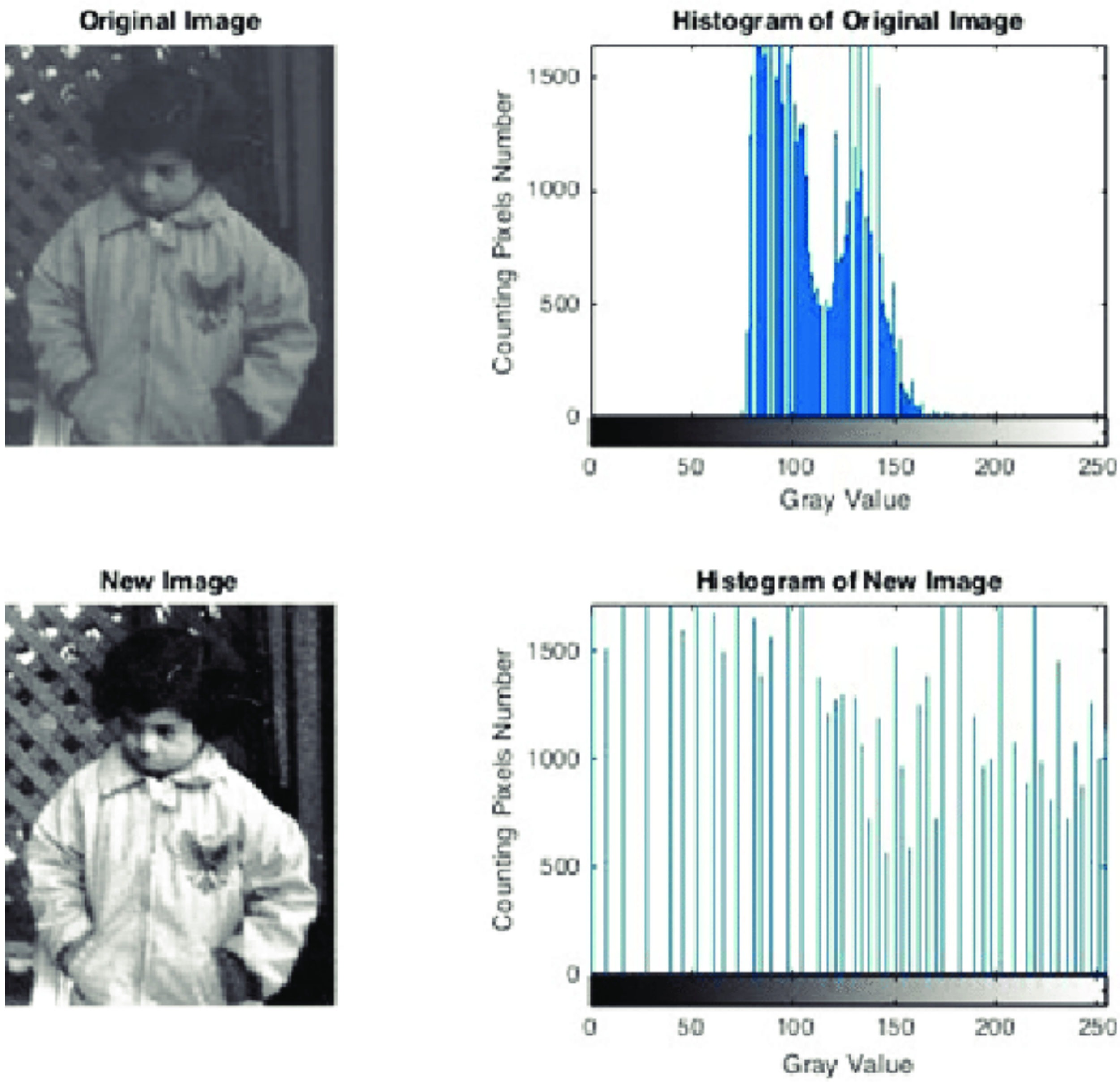
New Histogram



Old Histogram



(https://www.tutorialspoint.com/dip/histogram_equalization.htm)



(https://www.researchgate.net/figure/Histogram-equalization-Matlab-Image-Processing-Toolbox-has-the-different-filter-types-as_fig8_305081059)

2- Contrast Stretching

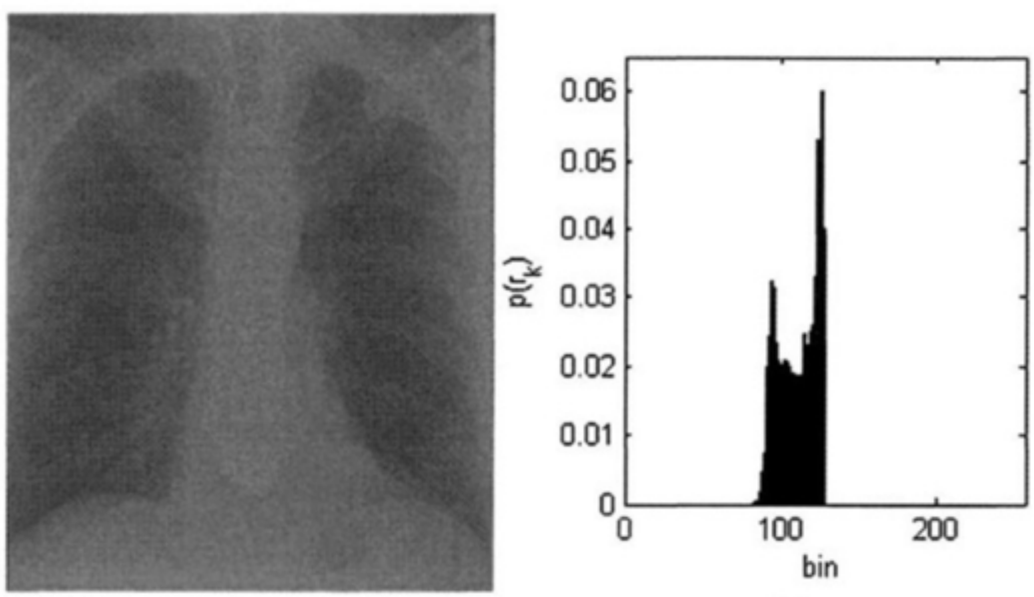
Contrast stretching, also known as intensity scaling, is an image enhancement technique used to improve the visibility of dark or bright areas in an image that may appear washed out or too dark. The technique works by mapping the original pixel intensities to new values that span the full range of intensity values, thereby increasing the contrast and brightness of the image.

The contrast stretching algorithm involves several steps. First, the minimum and maximum pixel intensity values in the image are computed. This can be done using the min() and max() functions in most programming languages or image processing software. Once the minimum and maximum values are known, the pixel intensities are scaled using the following mapping function:

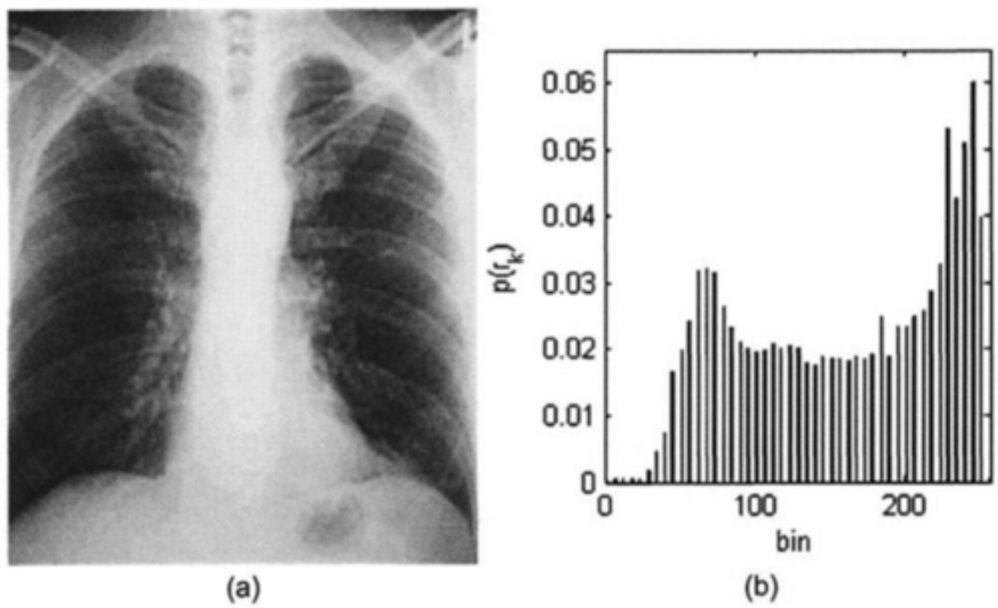
s = (r - min_val) * (L-1) / (max_val - min_val)

where s is the new pixel intensity value, r is the original pixel intensity value, L is the maximum intensity value (i.e., 256 for an 8-bit grayscale image), min_val is the minimum pixel intensity value in the image, and max_val is the maximum pixel intensity value in the image. The mapping function scales the original pixel intensities to new values that span the full range of intensity values, resulting in an image with improved contrast and brightness.

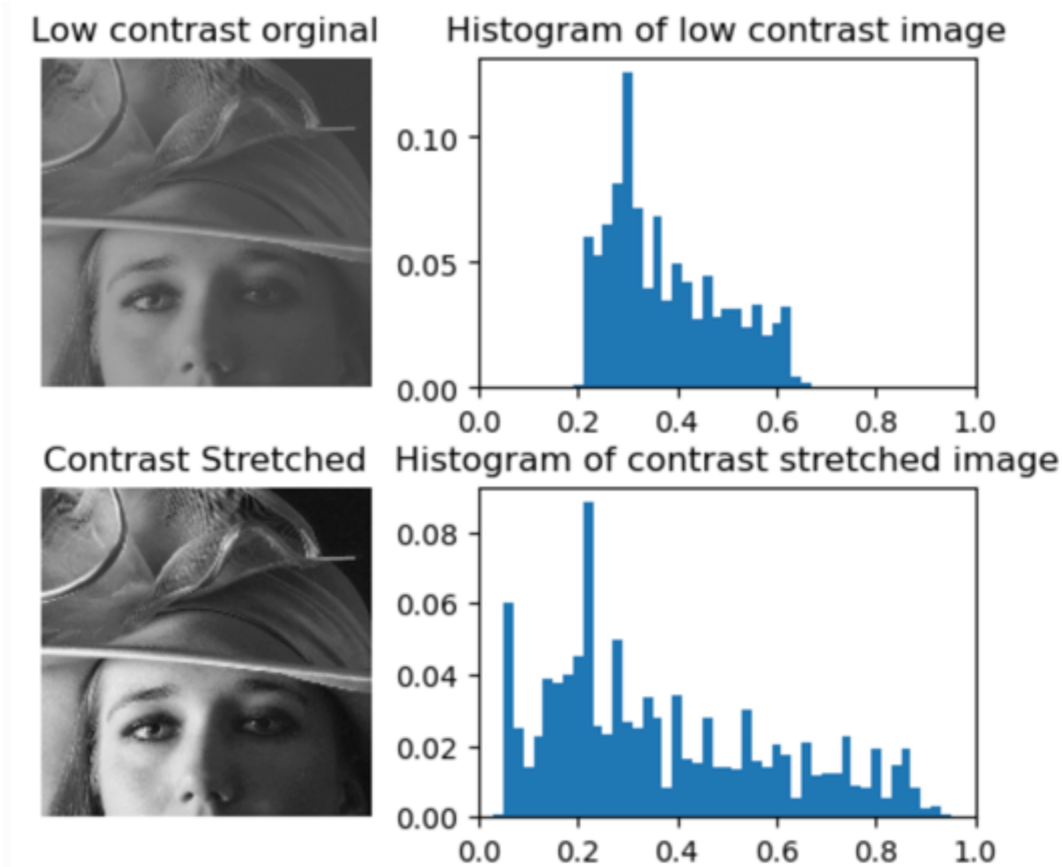
Contrast stretching is a simple and effective technique for enhancing the visual quality of digital images, but it has some limitations. In particular, it may produce artifacts such as over-enhancement and noise amplification in regions of the image with low contrast or high noise levels. To address these limitations, several variations and extensions of contrast stretching have been proposed, such as histogram equalization and adaptive contrast stretching.



(a) (b)



(http://what-when-how.com/embedded-image-processing-on-the-tms320c6000-dsp/contrast-stretching-image-processing/)



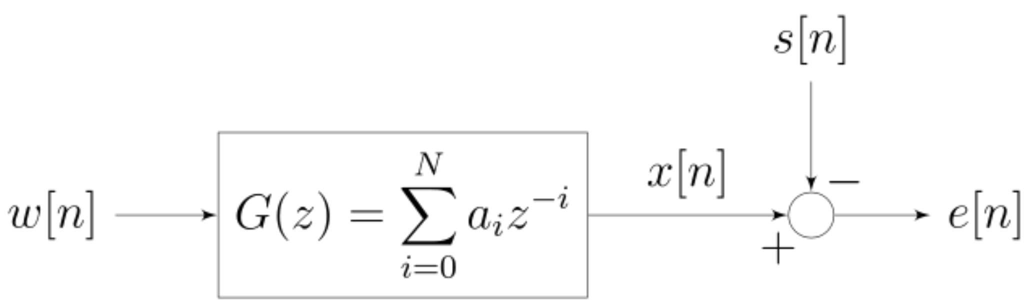
(https://staff.fnwi.uva.nl/r.vandenboomgaard/ComputerVision/LectureNotes/IP/PointOperators/ImageStretching.html)

3- Noise Reduction

Noise reduction aims at removing or suppressing unwanted variations in image intensity that may arise from various sources, such as sensor noise, compression artifacts, or environmental factors. Several techniques have been proposed for noise reduction, including spatial filtering, frequency domain filtering, and wavelet-based denoising.

Spatial filtering techniques operate on the image itself and involve the application of a filter to each pixel or local neighborhood of pixels. The filter is designed to smooth the image while preserving the underlying structure and edges. A common spatial filtering technique for noise reduction is the Gaussian filter, which applies a weighted average to each pixel based on the values of its neighboring pixels. The Gaussian filter is designed to preserve the high-frequency content of the image while removing the low-frequency noise.

Frequency domain filtering techniques operate in the frequency domain, where the image is represented as a sum of sinusoidal waves of different frequencies and amplitudes. The goal of frequency domain filtering is to remove or suppress the noise components in the image spectrum while preserving the important image features. A common frequency domain filtering technique for noise reduction is the Wiener filter, which applies a weighted average to each frequency component of the image based on the noise power and the signal-to-noise ratio.



Block diagram view of the FIR Wiener filter for discrete series. An input signal w[n] is convolved with the Wiener filter g[n] and the result is compared to a reference signal s[n] to obtain the filtering error e[n]. (https://www.wikiwand.com/en/Wiener_filter#:~:text=In%20signal%20processing%2C%20the%20Wiener,noise%20spectra%2C%20and%20additive%20noise.)

Wavelet-based denoising techniques operate in a multiresolution framework, where the image is decomposed into a series of wavelet coefficients at different scales and orientations. The wavelet coefficients are then thresholded to remove the noise components while preserving the important image features. A common wavelet-based denoising technique is the wavelet shrinkage algorithm, which applies a soft threshold to the wavelet coefficients based on their magnitudes and a threshold parameter.

Noise reduction is an essential task in digital image processing, as it can significantly improve the visual quality and accuracy of images in a wide range of applications, from medical imaging and scientific imaging to multimedia and surveillance.

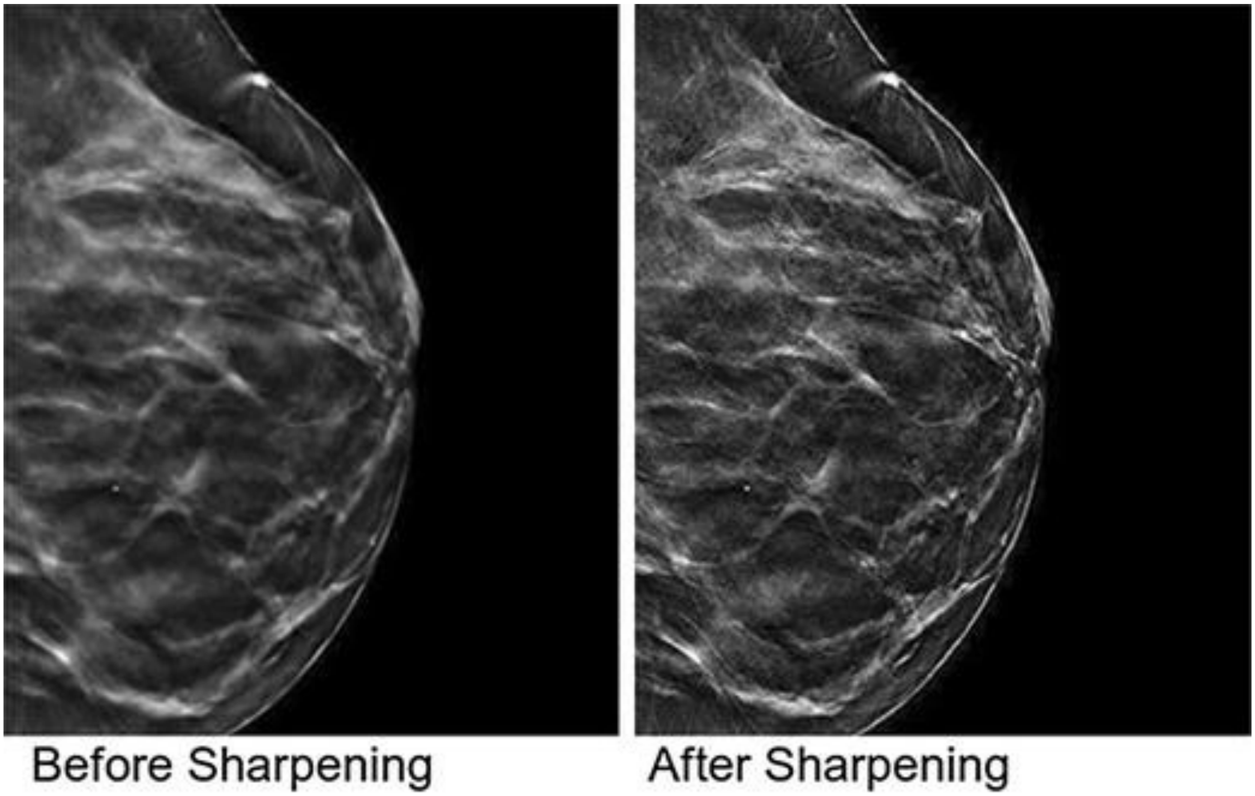
4- Sharpening

Sharpening is a type of image enhancement technique that is used to improve the clarity and definition of an image. The goal of sharpening is to increase the contrast between adjacent pixels and make the edges of objects in the image more distinct, which can lead to better visualization and interpretation of the image.

There are several different methods for sharpening, including unsharp masking, high-pass filtering, and edge enhancement. Unsharp masking involves creating a blurred version of the image, subtracting it from the original image, and then adding the resulting difference image back to the original image. This technique can be effective at enhancing the edges of objects in the image. High-pass filtering involves filtering the image to remove low-frequency information and emphasize high-frequency information, which can also lead to improved edge detection. Edge enhancement involves amplifying the contrast at the edges of objects in the image, making them more visible and distinct.

Sharpening is a commonly used technique in medical image processing, where it can be used to improve the visualization and interpretation of images from a wide range of modalities, including MRI, CT, and ultrasound. It can be particularly useful for enhancing subtle details in the image and aiding in the detection and diagnosis of medical conditions.

While sharpening can be a powerful tool in medical image processing, it is important to use it judiciously, as over-sharpening can lead to artifacts and other distortions in the image. Researchers and clinicians must balance the benefits of sharpening with the potential risks and limitations of the technique, and use it in conjunction with other image enhancement and processing techniques to optimize the diagnostic value of medical images.



(Sharpness Improvement for Medical Images Using a New Nimble Filter, Zohair Al-Ameen)

Image Filtering

Image filtering aims at modifying or enhancing the visual content of an image by altering the intensity values of its pixels. The goal of image filtering is to extract useful information from the image, remove noise or artifacts, and enhance the visual quality of the image for further processing or analysis.

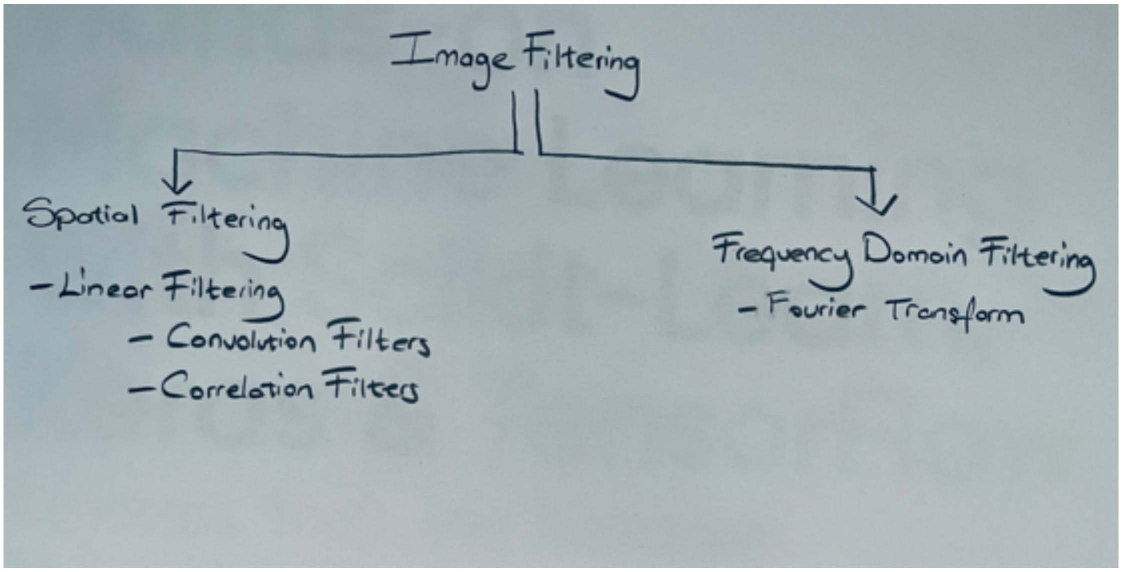
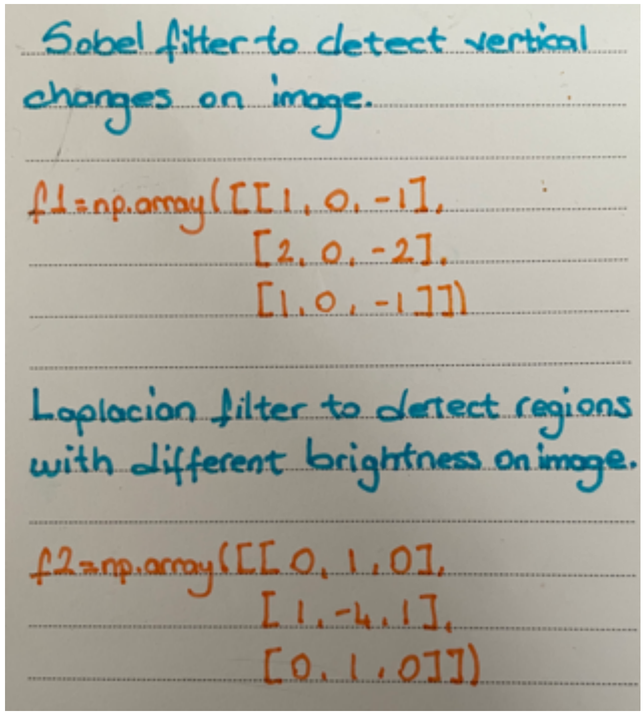


Image filtering techniques can be classified into two main categories: spatial filtering and frequency domain filtering. Spatial filtering techniques operate on the image itself and involve the application of a filter to each pixel or local neighborhood of pixels. The filter is designed to modify the pixel intensity values based on the values of its neighboring pixels. A common spatial filtering technique is the linear filter, which applies a weighted average to each pixel based on the values of its neighboring pixels. The weights are specified by a filter kernel or mask, which defines the shape and size of the filter.



Frequency domain filtering techniques operate in the frequency domain, where the image is represented as a sum of sinusoidal waves of different frequencies and amplitudes. The goal of frequency domain filtering is to modify the frequency components of the image spectrum while preserving the important image features. A common frequency domain filtering technique is the Fourier transform, which transforms the image from the spatial domain to the frequency domain. The Fourier transform can be used to visualize the frequency content of the image, remove noise or artifacts, and enhance the visual quality of the image.

1- Linear Filters

Linear filters are a class of image filters that operate on the intensity values of an image in a linear fashion. Linear filters are designed to modify the pixel intensity values based on the values of their neighboring pixels. The filter kernel or mask specifies the shape and size of the filter and determines the weights that are applied to the pixel values.

Linear filters can be classified into two main types: convolution filters and correlation filters. Convolution filters are the most common type of linear filters used in digital image processing. Convolution filters operate on the image by sliding the filter kernel over the image and computing a weighted sum of the pixel values under the kernel at each position. The weighted sum is then assigned as the new pixel value at that position.

Correlation filters operate in a similar way to convolution filters but without the flipping of the filter kernel. Correlation filters compute a weighted sum of the pixel values under the kernel at each position without reversing the kernel. Correlation filters are mainly used for template matching and feature detection in images.

"The basic difference between Correlation and convolution is:
Correlation is a measurement of the similarity between two signals/sequences.
Convolution is a measurement of the effect of one signal on the other signal.

The mathematical calculation of correlation is the same as convolution in time domain, except that the signal is not reversed, before the multiplication process. If the filter is symmetric then the output of both the expression would be the same."
(https://www.researchgate.net/post/Difference_between_convolution_and_correlation#:~:text=Correlation%20is%20measurement%20of%20the,reversed%2C%20before%20the%20multiplication%20process.)

2D Convolution

1	2	3
4	5	6
7	8	9

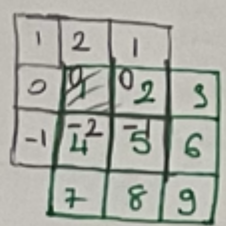
input

-1	-2	-1
0	0	0
1	2	1

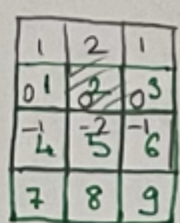
Kernel

-13	-20	-17
-18	-24	-18
13	20	17

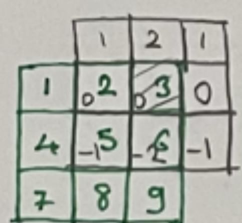
output



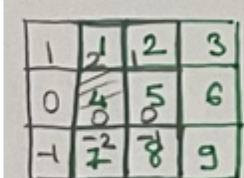
$$(0.1)+(0.2)+(4.-2)+(5.-1) = -13$$



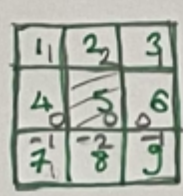
$$(0.1)+(0.2)+(0.3)+(4.-1)+(5.-2)+(6.-1) = -20$$



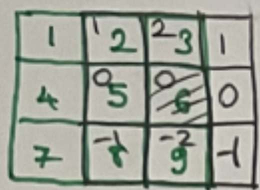
$$(0.2)+(0.3)+(5.-1)+(6.-2) = -17$$



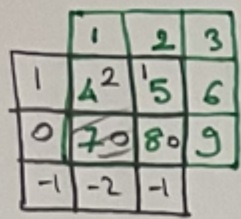
$$(2.1)+(1.2)+(4.0)+(5.0)+(7.-2)+(8.-1) = -18$$



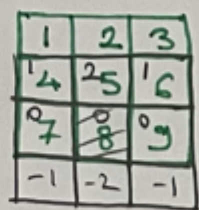
$$(1.1)+(2.2)+(3.1)+(7.-1)+(8.-2)+(9.-1) = -24$$



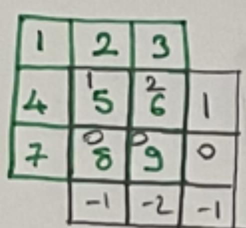
$$(2\cdot 1)+(3\cdot 2)+(8\cdot -1)+(9\cdot -2)=-18$$



$$(4\cdot 2)+(5\cdot 1)=13$$



$$(4\cdot 1)+(5\cdot 2)+(6\cdot 1)=20$$



$$(5\cdot 1)+(6\cdot 2)=17$$

-13	-20	-17
-18	-24	-18
13	20	17

Output dimension is calculated by following equations:

$$height_{output} = \frac{height_{input} - f_{size} + 2 * pad}{Step} + 1$$

$$width_{output} = \frac{width_{input} - f_{size} + 2 * pad}{step} + 1$$

Common examples of linear filters include the mean filter, Gaussian filter, and Sobel filter. The mean filter is a simple low-pass filter that replaces each pixel with the average value of its neighboring pixels. The Gaussian filter is a more sophisticated low-pass filter that applies a Gaussian distribution to the weights of the filter kernel, which results in a smoother and more natural-looking image. The Sobel filter is an edge detection filter that highlights the edges and contours in the image by computing the gradient magnitude of the image intensity values.

Gaussian filter is a low-pass filter that is used to smooth an image by reducing the high-frequency components. It is based on the Gaussian distribution, and its values are computed using a Gaussian kernel. Sobel filter, on the other hand, is a high-pass filter that is used to detect edges in an image by computing the gradient of the image. It consists of two kernels, one for computing the horizontal gradient and another for the vertical gradient.

Fourier Transform

The Fourier transform is used to decompose a signal or image into its constituent frequency components. The Fourier transform allows us to represent a signal or image as a sum of sine and cosine waves of different frequencies, amplitudes, and phases. The Fourier transform provides a powerful way to analyze the frequency content of a signal or image, and can be used for tasks such as filtering, compression, and feature extraction.

The Fourier transform can be applied to one-dimensional signals, such as audio signals, as well as two-dimensional signals, such as images. The two-dimensional Fourier transform of an image converts the image from the spatial domain to the frequency domain. The Fourier transform maps the intensity values of each pixel to a complex number that represents the amplitude and phase of the corresponding frequency component. The magnitude of the complex number represents the amplitude of the frequency component, while the phase represents the relative phase of the component.

The inverse Fourier transform can be used to convert an image from the frequency domain back to the spatial domain. The inverse Fourier transform allows us to reconstruct an image from its frequency components, and provides a way to modify the frequency content of an image. The Fourier transform can be used in digital image processing, with a wide range of applications in areas such as image filtering, compression, and feature extraction.

In signal processing, the Fourier transform is used for tasks such as filtering, compression, and feature extraction in applications such as audio and speech processing, radar and sonar systems, and biomedical signal analysis.

In image processing, the Fourier transform is used for tasks such as image filtering, compression, and feature extraction. The Fourier transform provides a way to analyze the frequency content of an image, which can be used to remove noise, enhance features, and compress the image. The Fourier transform is widely used in applications such as medical imaging, remote sensing, and computer vision.

"If f(m, n) is a function of two discrete spatial variables m and n, then the two-dimensional Fourier transform of f(m, n) is defined by the relationship

$$F(\omega_1, \omega_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(m,n) e^{-j\omega_1 m} e^{-j\omega_2 n}.$$

The variables ω_1 and ω_2 are frequency variables; their units are radians per sample. $F(\omega_1,\omega_2)$ is often called the *frequency-domain* representation of $f(m, n)$. $F(\omega_1, \omega_2)$ is a complex-valued function that is periodic both in ω_1 and ω_2, with period 2π. Because of the periodicity, usually only the range $-\pi \le \omega 1, \omega 2 \le \pi$ is displayed. Note that $F(0, 0)$ is the sum of all the values of $f(m ,n)$. For this reason, $F(0,0)$ is often called the *constant component* or *DC component* of the Fourier transform. (DC stands for direct current; it is an electrical engineering term that refers to a constant-voltage power source, as opposed to a power source whose voltage varies sinusoidally.)

The inverse of a transform is an operation that when performed on a transformed image produces the original image. The inverse two-dimensional Fourier transform is given by

$$f(m,n) = \frac{1}{4\pi^2} \int_{\omega_1=-\pi}^{\pi} \int_{\omega_2=-\pi}^{\pi} F(\omega_1, \omega_2) e^{j\omega_1 m} e^{j\omega_2 n} d\omega_1 d\omega_2.$$

Roughly speaking, this equation means that f(m, n) can be represented as a sum of an infinite number of complex exponentials (sinusoids) with different frequencies. The magnitude and phase of the contribution at the frequencies (ω1, ω2) are given by F(ω1, ω2)." (https://www.mathworks.com/help/images/fourier-transform.html)

Image Segmentation

Image segmentation is the process of dividing an image into multiple regions or objects based on their visual properties, such as color, texture, and shape. Image segmentation is an essential task in many applications, such as object detection, tracking, and recognition.

Thresholding

Thresholding is a simple and effective image segmentation technique that partitions an image into foreground and background regions based on a threshold value. The threshold value is chosen such that pixel intensities above the threshold are classified as foreground, while those below the threshold are classified as background. Thresholding is particularly useful for images with clear contrast between foreground and background regions.

There are several thresholding methods, including global thresholding, local thresholding, and adaptive thresholding. Global thresholding involves choosing a single threshold value for the entire image, which can be determined manually or automatically using techniques such as Otsu's method. Local thresholding involves choosing different threshold values for different regions of the image based on local statistics, such as mean or standard deviation. Adaptive thresholding is a variant of local thresholding that adjusts the threshold value based on the local image properties, such as illumination and contrast.

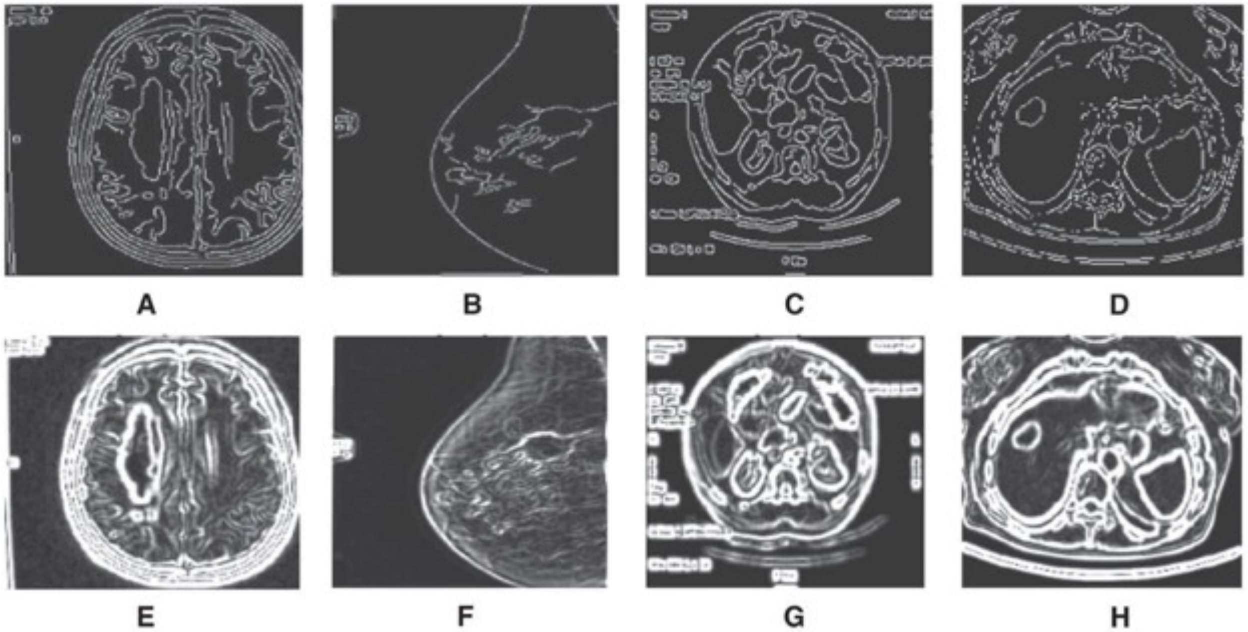
Thresholding has several advantages, including simplicity, speed, and applicability to a wide range of images. However, thresholding also has some limitations, particularly when dealing with images with complex foreground and background regions, or with low contrast or uneven illumination. In such cases, other image segmentation techniques such as edge detection or clustering may be more suitable. Nonetheless, thresholding remains a powerful and widely used image segmentation technique in digital image processing.

Edge Detection

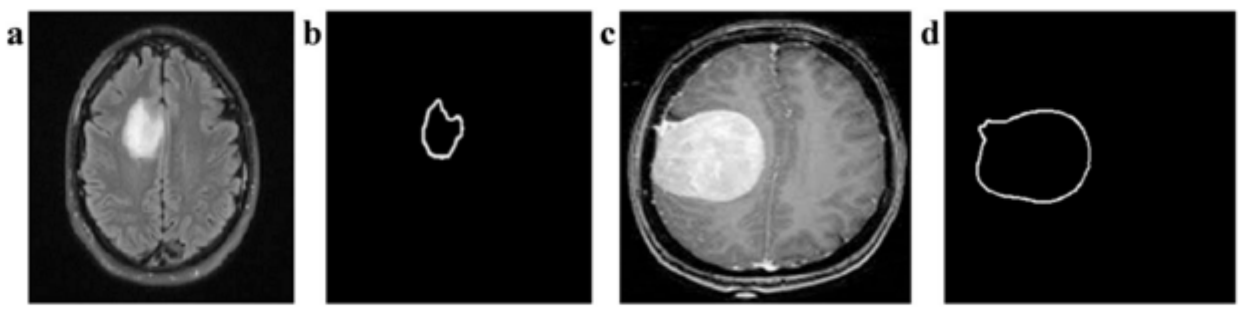
Edge detection is a common image segmentation technique that involves detecting the edges or boundaries between regions in an image. Edge detection algorithms work by identifying changes in the intensity values of adjacent pixels, which correspond to the edges or boundaries in the image. Edges can be defined as abrupt changes in image intensity or as areas with high gradient magnitude.

There are several edge detection algorithms, including the Sobel operator, Canny edge detector, and Laplacian of Gaussian filter. The Sobel operator calculates the gradient magnitude in the horizontal and vertical directions and combines them to form a gradient magnitude image. The Canny edge detector is a multi-stage algorithm that involves smoothing the image with a Gaussian filter, calculating the gradient magnitude and direction, non-maximum suppression, and hysteresis thresholding. The Laplacian of Gaussian filter convolves the image with a Gaussian filter and calculates the Laplacian of the resulting image, which highlights areas with high curvature or rapid changes in intensity.

Edge detection has several advantages, including the ability to identify object boundaries and salient features, and the capability to reduce the amount of data in an image. However, edge detection also has some limitations, including sensitivity to noise and variability in illumination, and the inability to segment images with complex structures and textures. Nonetheless, edge detection remains a powerful and widely used image segmentation technique in digital image processing.



(https://www.researchgate.net/figure/Edge-Detection-Algorithms-for-Boundary-Detection-in-Medical-Images-A-D-Canny-Edge_fig4_325750965)



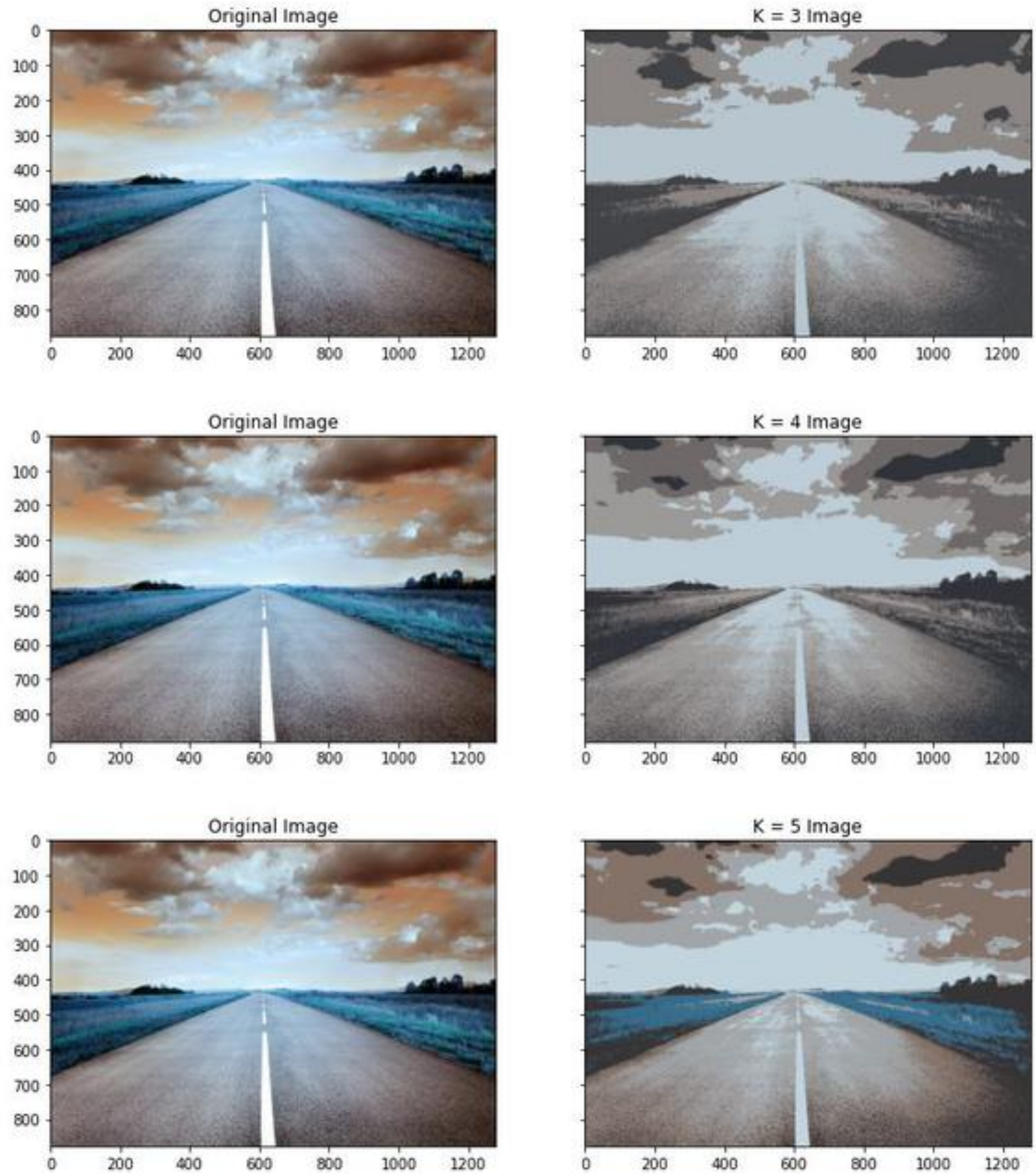
(Edge detection in MRI brain tumor images based on fuzzy C-means clustering, Alexander Zotin et. al.)

Clustering

Clustering is a common image segmentation technique that involves partitioning an image into distinct regions or clusters based on the similarity of the pixel values. Clustering algorithms work by grouping pixels with similar attributes, such as color or texture, into clusters, and assigning each pixel to the cluster with the closest attribute. The resulting clusters can represent regions of similar or dissimilar pixel values, which can be used to identify and segment objects in the image.

There are several clustering algorithms, including k-means clustering, fuzzy c-means clustering, and hierarchical clustering. K-means clustering is a simple and fast algorithm that partitions the image into k clusters, where k is a user-defined parameter. Fuzzy c-means clustering is a variant of k-means that allows pixels to belong to multiple clusters with varying degrees of membership. Hierarchical clustering involves grouping pixels based on their similarity and then iteratively merging or splitting clusters until a stopping criterion is met.

Clustering has several advantages, including the ability to segment images with complex structures and textures, and the capability to identify objects based on their attributes rather than their spatial location. However, clustering also has some limitations, including sensitivity to the choice of similarity measure and the number of clusters, and the tendency to generate over-segmentation or under-segmentation in some cases. Nonetheless, clustering remains a powerful and widely used image segmentation technique in digital image processing.



(https://www.geeksforgeeks.org/image-segmentation-by-clustering/)

Overall, image segmentation is a fundamental task in digital image processing, with a wide range of applications in areas such as computer vision, remote sensing, and medical imaging. Different image segmentation techniques such as thresholding, edge detection, and clustering methods can be used to partition an image into multiple regions or objects, depending on the visual properties of the image and the specific application requirements.

Image Registration

Image registration is a common image processing technique that involves aligning and merging multiple images of the same scene or object. Image registration algorithms work by transforming one or more images to match a reference image based on some criterion, such as maximizing the similarity between corresponding features or minimizing the difference between pixel intensities. The resulting aligned images can be used to create composite images, enhance image resolution, or remove motion artifacts.

There are several image registration algorithms, including image warping, feature-based registration, and intensity-based registration. Image warping involves transforming one or more images using a geometric transformation, such as translation, rotation, scaling, or affine transformation, to align the images with a reference image. Feature-based registration involves identifying and matching salient features in the images, such as corners, edges, or blobs, and using the correspondences to compute a transformation that aligns the images. Intensity-based registration involves minimizing the difference between the pixel intensities of the images using optimization techniques, such as gradient descent or Powell's method.

Image registration has several advantages, including the ability to create composite images with high spatial resolution and reduced motion artifacts, and the capability to enhance the quality of medical or remote sensing images. However, image registration also has some limitations, including sensitivity to the choice of similarity measure and the presence of noise or outliers in the images. Nonetheless, image registration remains a powerful and widely used image processing technique in digital image processing.

Introduction to Medical Image Processing

Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is a non-invasive diagnostic imaging technique used to visualize the internal structures of the body. MRI uses a strong magnetic field and radio waves to generate detailed images of organs, tissues, and bones.

The basic principle of MRI is that certain atomic nuclei, such as hydrogen nuclei in water molecules, have a property called spin. When placed in a strong magnetic field, the nuclei align themselves with the magnetic field. Radio waves are then used to perturb the alignment of these nuclei, causing them to emit a signal that can be detected by specialized sensors. By analyzing the signals emitted by the nuclei, MRI machines can reconstruct detailed images of the body.

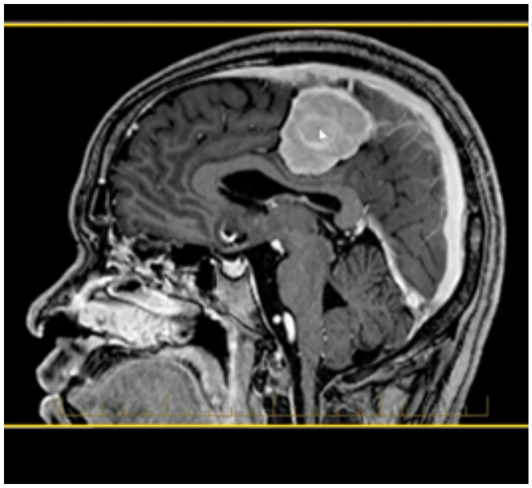
MRI provides high resolution images of soft tissues that are difficult to visualize with other imaging techniques, such as X-rays or CT scans. MRI can be used to diagnose a variety of conditions, including brain and spinal cord injuries, tumors, joint injuries, and cardiovascular disease. It can also be used to monitor the effectiveness of treatments and to guide surgical procedures.

There are different types of MRI machines, including closed and open MRI machines. Closed MRI machines are cylindrical in shape and require the patient to lie down inside the machine for the duration of the scan. Open MRI machines are less confining and may be more suitable for patients who are claustrophobic or who cannot lie down for extended periods of time.

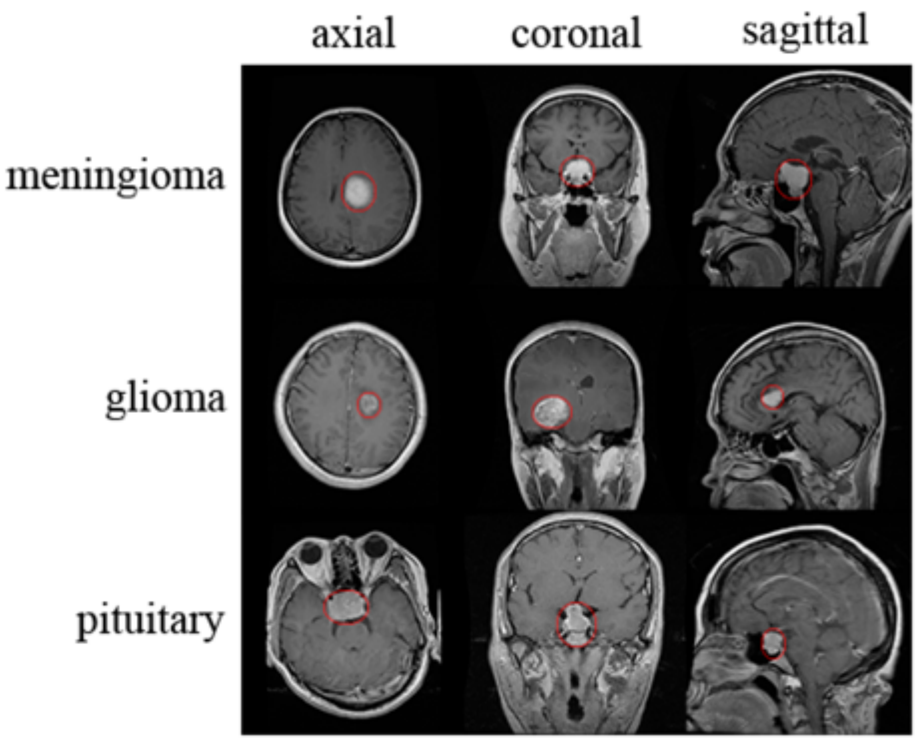
MRI is generally considered a safe imaging technique, but patients with certain medical devices or conditions, such as pacemakers or metallic implants, may not be able to undergo MRI scans. It is important to inform the medical staff of any medical devices or conditions before undergoing an MRI scan.

“Radio waves cause these aligned atoms to produce faint signals, which are used to create cross-sectional MRI images — like slices in a loaf of bread.
The MRI machine can also produce 3D images that can be viewed from different angles. “ (https://www.mayoclinic.org/tests-procedures/mri/about/pac-

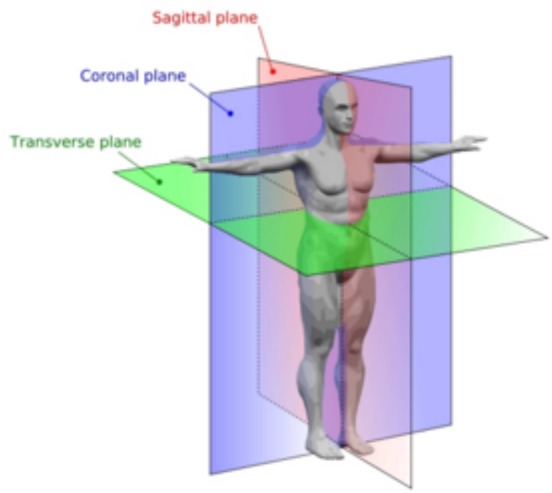
20384768#:~:text=Magnetic%20resonance%20imaging%20(MRI)%20is,large%2C%20tube%2Dshaped%20magnets.)



(https://mrionline.com/wp-content/uploads/mri-mastery-series-brain-tumors.png)



(https://www.mdpi.com/2076-3417/10/6/1999)



- Axial plane = transverse plane: perpendicular to the body long axis
- Sagittal: bisects the left from the right side [from new latin *sagitta* = arrow]
- Coronal: bisects the front from the back [from latin *corona* = crown]

(https://www.uio.no/studier/emner/matnat/ifi/INF-GEO4310/h11/undervisningsmateriale/medcal_imaging--students_handout.pdf)

Computed Tomography (CT)

Computed Tomography (CT) is a medical imaging technique that uses X-rays to produce detailed images of the body. CT is based on the same principle as conventional X-ray imaging, but it uses a more sophisticated imaging system to generate cross-sectional images of the body.

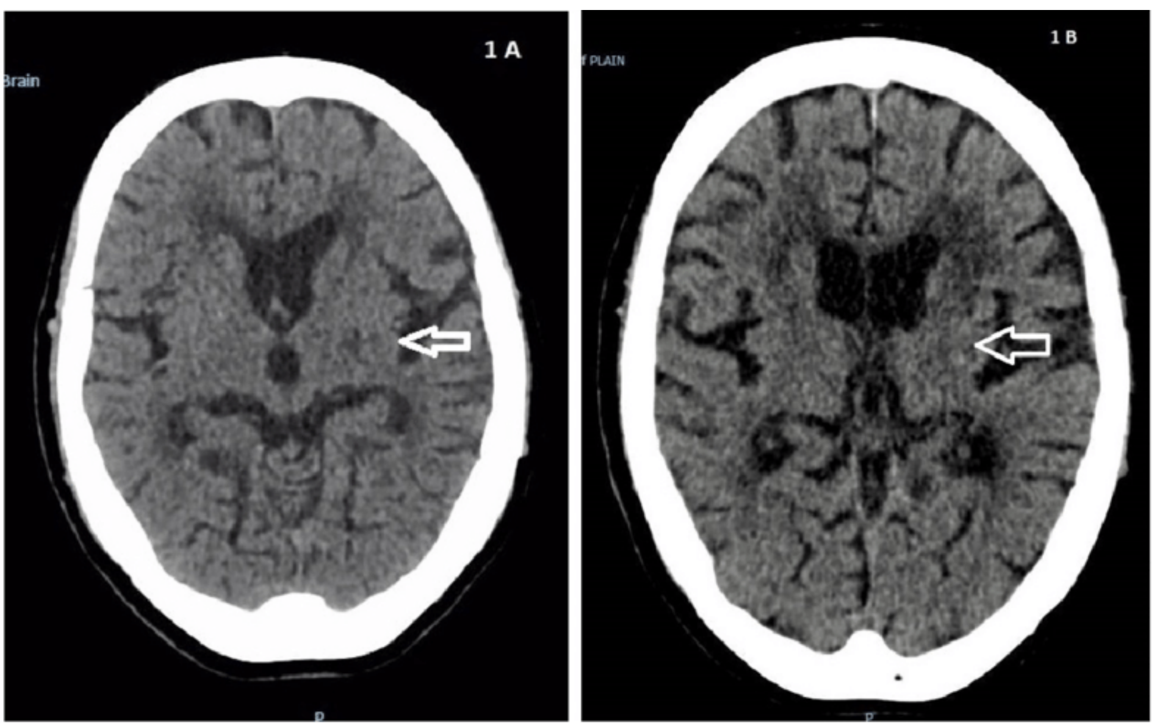
In CT imaging, the X-ray source and detectors rotate around the patient, while the patient remains stationary on a table. As the X-ray source and detectors rotate, multiple X-ray images are acquired from different angles around the body. These images are then processed by a computer to create detailed cross-sectional images of the body.

CT provides high-resolution images of bones, soft tissues, and blood vessels, making it a valuable tool for diagnosing a wide range of medical conditions, such as trauma, cancer, and cardiovascular disease. CT is also used to guide biopsies and other minimally invasive procedures.

CT scans can be performed on different parts of the body, including the head, chest, abdomen, and pelvis. Some CT scans may require the use of a contrast material, which is injected into the body to enhance the visibility of certain structures. The contrast material may be administered orally, intravenously, or rectally, depending on the area of the body being imaged.

While CT scans are generally considered safe, they do expose patients to ionizing radiation, which can increase the risk of cancer over time. However, the benefits of CT imaging usually outweigh the risks of radiation exposure, particularly in cases where the scan is necessary for diagnosing or treating a medical condition.

Modern CT scanners are designed to minimize radiation exposure while still producing high-quality images. Techniques such as low-dose CT and iterative reconstruction can help reduce the amount of radiation exposure associated with CT scans.



(https://www.researchgate.net/publication/321484469/figure/fig1/AS:591564053164032@1518051269842/Computed-Tomography-CT-of-the-Brain-1A-left-CT-brain-on-first-presentation-showing.png)

Positron Emission Tomography (PET)

Positron Emission Tomography (PET) is a medical imaging technique that uses a small amount of a radioactive tracer to produce detailed images of the body. PET is based on the principle that certain substances in the body, such as glucose, are metabolized differently in normal and abnormal tissues.

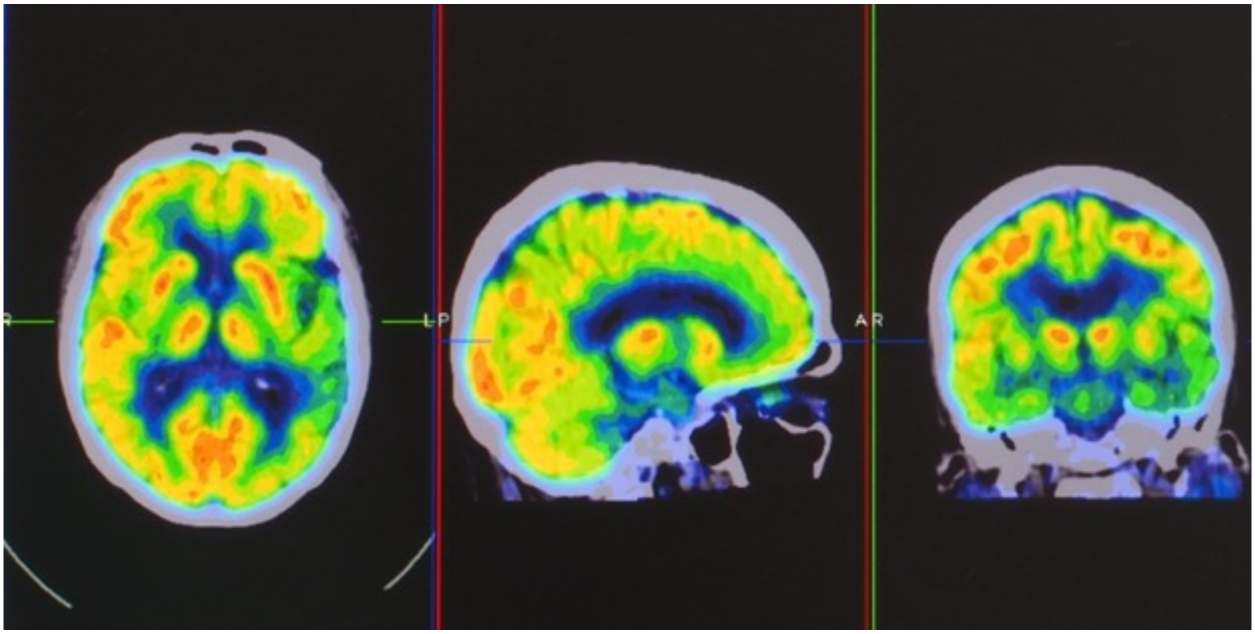
In PET imaging, a small amount of a radioactive tracer is injected into the patient's bloodstream. The tracer emits positrons, which are a type of subatomic particle. When the positrons encounter electrons in the body, they annihilate each other, releasing gamma rays. These gamma rays are detected by specialized sensors, which are used to create 3D images of the body.

PET is often used to diagnose cancer and to evaluate the extent of cancer spread. It can also be used to diagnose neurological conditions, such as Alzheimer's disease and epilepsy, by imaging the metabolism of glucose in the brain.

PET scans can be performed on different parts of the body, depending on the specific medical condition being evaluated. Some PET scans may require the use of a contrast material, which is injected into the body to enhance the visibility of certain structures.

While PET scans are generally considered safe, they do expose patients to a small amount of radiation. However, the radiation exposure associated with PET scans is typically lower than that of CT scans, and the benefits of the imaging procedure usually outweigh the risks.

PET imaging can be combined with CT imaging to create a technique called PET-CT. PET-CT combines the metabolic information obtained from PET with the anatomical information obtained from CT, providing a more complete picture of the body's tissues and structures. PET-CT is often used in cancer diagnosis and treatment planning.

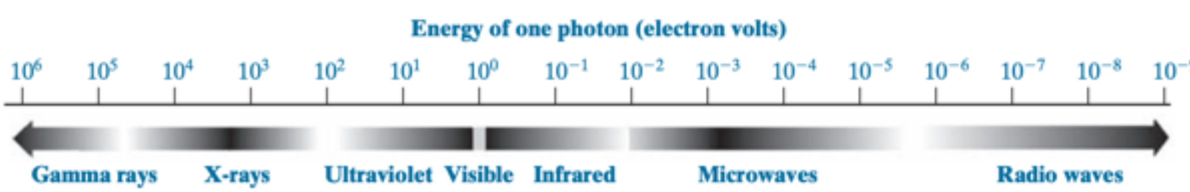


(https://jpu.edu/positron-emission-tomography-certificate/)

Single-Photon Emission Computed Tomography (SPECT)

Single-Photon Emission Computed Tomography (SPECT) is a medical imaging technique that uses a radioactive tracer to produce detailed images of the body's internal structures. SPECT is based on the same principle as PET imaging, but it uses a different type of tracer and imaging technology.

In SPECT imaging, a small amount of a radioactive tracer is injected into the patient's bloodstream. The tracer emits gamma rays, which are detected by specialized cameras as the patient lies on a table that moves through the camera. The cameras capture multiple images from different angles around the body, which are then processed by a computer to create detailed 3D images of the body's internal structures.



(Digital Image Processing 4th Edition, Rafael C. Gonzalez, Richard E. Woods)

SPECT imaging is often used to diagnose and monitor conditions such as heart disease, brain disorders, and bone disorders. It is particularly useful in imaging structures deep within the body, such as the heart and brain.

SPECT can be combined with CT imaging to create a technique called SPECT-CT. SPECT-CT combines the functional information obtained from SPECT with the anatomical information obtained from CT, providing a more complete picture of the body's tissues and structures.

While SPECT imaging is generally considered safe, it does expose patients to a small amount of radiation. However, the radiation exposure associated with SPECT is typically lower than that of CT scans, and the benefits of the imaging procedure usually outweigh the risks.

Recent advances in SPECT technology have led to the development of new tracers and imaging techniques that are more sensitive and specific, allowing for earlier and more accurate diagnosis of medical conditions.

Ultrasound

Ultrasound is a medical imaging technique that uses high-frequency sound waves to produce images of the body's internal structures. Ultrasound imaging is non-invasive, painless, and does not involve the use of ionizing radiation, making it a safe imaging option for many patients.

In ultrasound imaging, a handheld transducer is placed on the skin or inside a body cavity, such as the vagina or rectum. The transducer emits high-frequency sound waves, which travel through the body and bounce back off the internal structures. The echoes are detected by the transducer and used to create images of the body.

Ultrasound imaging is commonly used to evaluate the development of a fetus during pregnancy. It is also used to diagnose and monitor conditions such as gallstones, kidney stones, and blood clots. In addition, ultrasound is often used to guide biopsies and other minimally invasive procedures.

Ultrasound can be performed on different parts of the body, including the abdomen, pelvis, and breasts. Some ultrasound exams may require the use of a contrast material, which is injected into the body to enhance the visibility of certain structures.

While ultrasound imaging is generally considered safe, it may not be appropriate for all patients or all conditions. For example, ultrasound may not be effective in imaging structures that are located deep within the body, such as the lungs or certain areas of the brain. In addition, the quality of ultrasound images may be affected by factors such as the patient's body habitus, the presence of gas or bone in the imaging area, or the presence of medical devices or implants.

Recent advances in ultrasound technology have led to the development of 3D and 4D ultrasound imaging, which provide more detailed images of the body's internal structures. These imaging techniques may be particularly useful in obstetrics and gynecology, as well as in the evaluation of certain musculoskeletal conditions.

(https://www.wikiwand.com/en/Ultrasound)

MRI, CT, PET, ultrasound, and SPECT are all medical imaging techniques that are used to visualize the body's internal structures for diagnostic purposes. While they share the common goal of providing detailed images of the body, they differ in terms of the technology used, the type of information obtained, and the clinical applications.

One of the primary differences between these imaging techniques is the type of energy used to create the images. MRI and ultrasound use non-ionizing radiation, while CT, PET, and SPECT use ionizing radiation. This has important implications for patient safety and radiation exposure, with MRI and ultrasound generally considered safer than CT, PET, and SPECT.

Another key difference is the type of information obtained from the images. MRI and ultrasound provide information about the structure and function of soft tissues, such as organs, muscles, and blood vessels, while CT, PET, and SPECT are better suited for imaging bone, lung, and brain function. PET and SPECT provide information about the metabolic activity of tissues, which can be useful in the diagnosis and treatment of cancer and neurological conditions.

The clinical applications of these imaging techniques also differ. MRI is often used to evaluate soft tissue injuries and diseases, such as tumors and neurological conditions. CT is commonly used to evaluate bone injuries, lung diseases, and to guide biopsies and other interventional procedures. PET and SPECT are frequently used in cancer diagnosis and treatment planning, while ultrasound is commonly used in obstetrics and gynecology, as well as in the evaluation of musculoskeletal and abdominal conditions.

Medical Imaging Formats

Medical imaging formats refer to the various file formats used to store medical images and associated metadata. There are several different formats commonly used in medical imaging, each with its own strengths and limitations. These formats can be broadly divided into two categories: vendor-specific formats and standardized formats.

Vendor-specific formats are proprietary formats developed by individual vendors for their imaging equipment. These formats are optimized for specific imaging modalities and may include proprietary compression algorithms that can reduce file size and improve transmission times. However, these formats are not always compatible with other vendors' equipment or software, which can limit the interoperability of medical images.

Standardized formats, such as DICOM (Digital Imaging and Communications in Medicine), are developed by international standards organizations and are designed to be interoperable across different equipment and software platforms. DICOM is a widely adopted format that includes not only the image data but also information about the patient, the imaging equipment, and the imaging protocol. Other standardized formats include NIfTI (Neuroimaging Informatics Technology Initiative) and Analyze, which are commonly used in neuroimaging research.

In addition to these formats, there are also emerging formats such as the Medical Imaging Data and Analysis Framework (MIDAF) and the Neuroimaging Data Model (NIDM) that are designed to address some of the limitations of existing formats, such as the lack of support for multi-modal imaging and the need for more standardized metadata. As medical imaging continues to evolve and new imaging modalities and analysis techniques are developed, it is likely that new formats will emerge to meet the changing needs of the field.

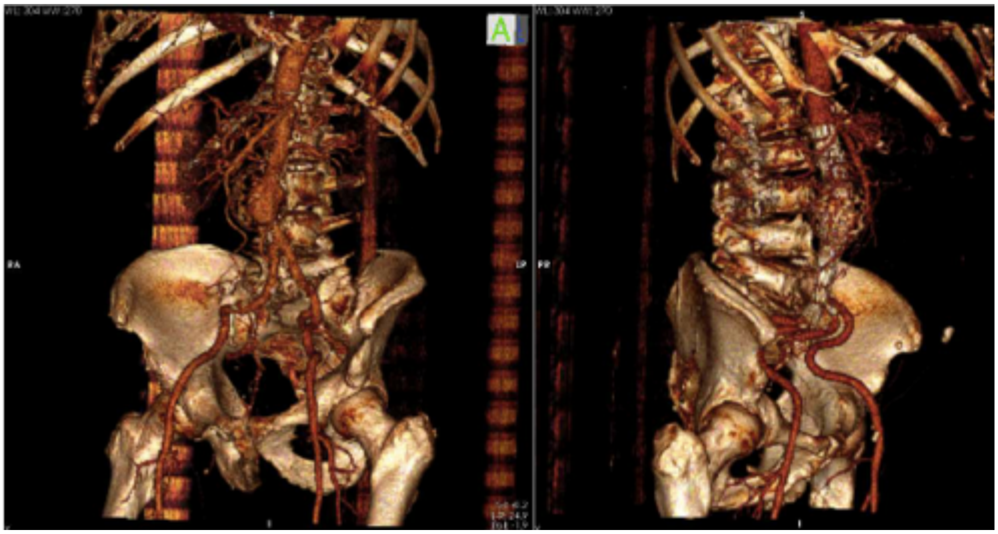
3D Imaging

Volumetric Rendering

Volumetric rendering is a technique used in 3D imaging and visualization to create a two-dimensional representation of a three-dimensional object or scene. This technique involves projecting a 3D image onto a 2D plane by tracing rays through the volume of the image and calculating the color and opacity of the material at each point along the ray. This creates a 2D image that provides information about the location, size, and shape of the internal structures of an object.

Volumetric rendering is commonly used in medical imaging to provide detailed images of internal organs and tissue structures. In this application, the 3D image is typically created using computed tomography (CT) or magnetic resonance imaging (MRI) scans, which capture a series of 2D images from different angles. These images are then combined to create a 3D image of the internal structure of the body. Volumetric rendering is used to visualize this 3D image in a way that allows physicians to view and analyze the internal structures of the body, such as organs, blood vessels, and tumors.

Volumetric rendering is also used in other fields, such as engineering and architecture, to visualize and analyze complex structures. In these applications, the 3D image may be created using computer-aided design (CAD) software or other modeling tools, and volumetric rendering can be used to create a 2D representation of the structure that provides insight into its internal features and characteristics. Overall, volumetric rendering is an important tool for visualizing and analyzing 3D data in a variety of fields and applications.



(https://www.researchgate.net/figure/3D-volume-rendering-of-CTA-series-of-pre-left-and-post-operative-right-study-of_fig1_264040838)

Surface Extraction

Surface extraction is a technique used in 3D imaging to create a surface representation of a three-dimensional object or scene. This technique involves extracting the surface of an object from a volumetric data set, such as those generated by CT or MRI scans, and creating a 3D model of the object's surface. This model can then be used for visualization, analysis, and further processing.

There are several methods used for surface extraction, including contouring, marching cubes, and surface fitting. Contouring involves extracting the surface by identifying points in the volumetric data where a specific value is reached, such as a specific intensity or density value. Marching cubes is a method that constructs a surface by dividing the volumetric data into small cubes and analyzing the data within each cube to determine if there is a surface present. Surface fitting involves analyzing the volumetric data to identify a mathematical function that best represents the surface of the object.

Surface extraction is commonly used in medical imaging to create 3D models of organs, tumors, and other structures for visualization and surgical planning. It is also used in computer graphics and animation to create realistic 3D models of objects and characters for video games, movies, and other applications. Surface extraction plays an important role in many fields that require the creation and manipulation of 3D models and can provide valuable insight into the internal structure of objects and their properties.

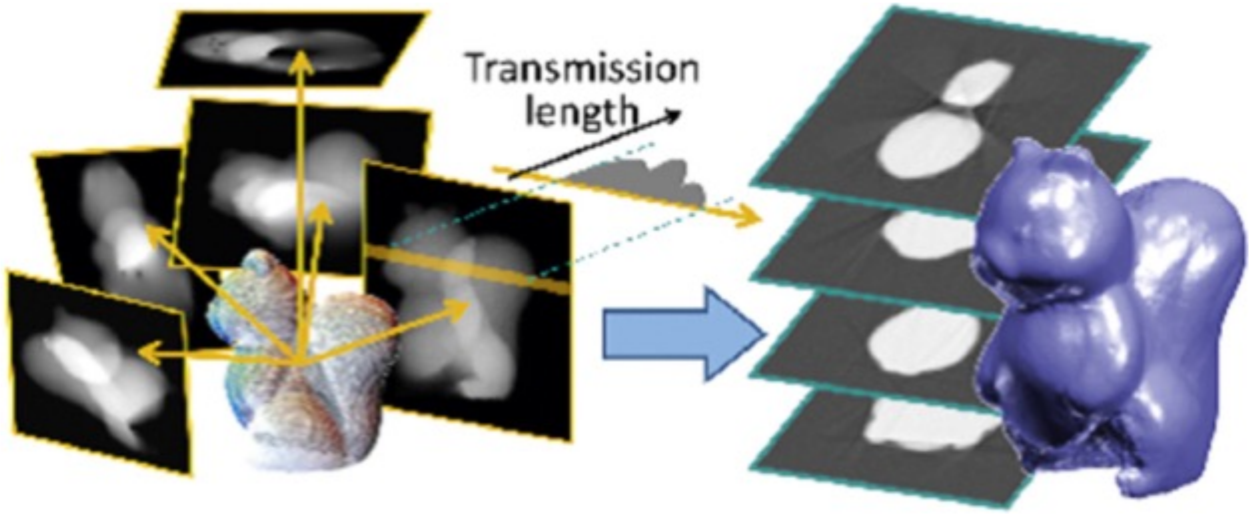
Tomographic Reconstruction

Tomographic reconstruction is a technique used in medical imaging, materials science, and other fields to create a 3D image of an object from a series of 2D images taken from different angles. This technique is commonly used in computed tomography (CT) and positron emission tomography (PET) to produce detailed 3D images of organs and tissues within the body.

The process of tomographic reconstruction involves using mathematical algorithms to combine the 2D images, or projections, taken from different angles into a single 3D image. These algorithms use information about the geometry of the imaging system, the positions and angles of the projections, and the properties of the object being imaged to reconstruct a detailed 3D model.

There are several methods used for tomographic reconstruction, including filtered back projection, algebraic reconstruction techniques, and iterative reconstruction methods. Filtered back projection is a commonly used technique that involves passing the projections through a filter to remove noise and artifacts and then back projecting the filtered data to create a 3D image. Algebraic reconstruction techniques and iterative reconstruction methods use mathematical models to iteratively refine the 3D image until it closely matches the original projections.

Tomographic reconstruction plays an important role in many fields that require the creation of detailed 3D images, such as medical imaging, materials science, and archaeology. It can provide valuable insight into the internal structure and properties of objects and can be used for diagnosis, treatment planning, and scientific research.



(https://www.sciencedirect.com/science/article/abs/pii/S0097849314001228)

Feature Extraction

Feature extraction is a technique used in image processing and computer vision to identify and isolate meaningful features or patterns in an image. The goal of feature extraction is to convert raw image data into a set of features that can be used for further analysis, such as object recognition, classification, or tracking.

The process of feature extraction involves selecting and extracting specific properties or characteristics of an image, such as edges, corners, textures, or colors, that are relevant to the task at hand. These features are often represented as numerical vectors that can be used as inputs to machine learning algorithms or other types of image processing techniques.

There are many different methods used for feature extraction, depending on the nature of the image data and the specific application. Some commonly used techniques include edge detection, corner detection, texture analysis, and histogram-based methods. These techniques can be used alone or in combination to extract a wide variety of features from images.

Feature extraction plays an important role in many fields, such as robotics, autonomous vehicles, medical imaging, and security systems. It allows computers and machines to analyze and understand images in a way that is similar to how humans perceive and interpret visual information.

Feature extraction is a critical step in medical image processing that involves extracting quantitative measures such as size, shape, and texture of regions of interest in medical images. These features can be used to differentiate between different tissues, identify abnormalities or lesions, and provide valuable information for diagnosis, treatment planning, and monitoring of medical conditions.

There are several different methods for feature extraction, including shape-based features, texture-based features, and intensity-based features. Shape-based features involve measuring geometric properties of regions of interest, such as area, perimeter, and compactness. Texture-based features involve analyzing the spatial arrangement of pixels and their intensity variations within a region of interest. Intensity-based features involve measuring the intensity distribution of pixels within a region of interest.

In medical imaging, feature extraction is used in a wide range of applications, such as tumor classification and grading, diagnosis of neurological conditions, and detection of bone fractures. It can also be used in image registration, where features extracted from multiple images can be used to align the images and facilitate comparison.

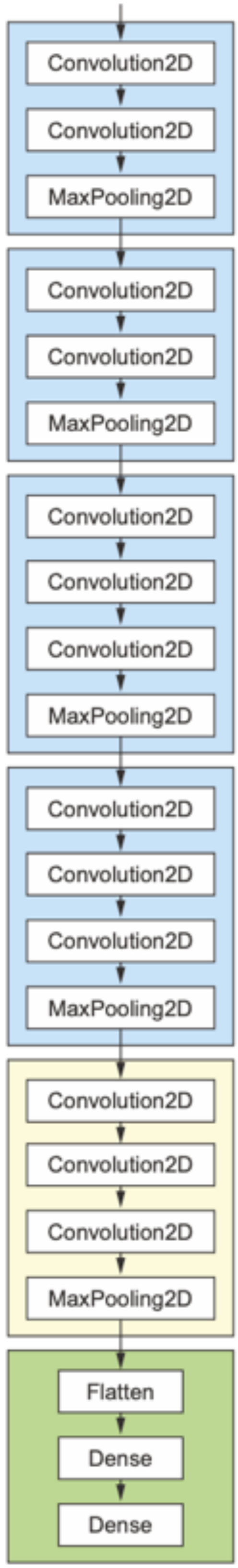
While feature extraction is a powerful tool in medical image processing, it can be challenging due to the complexity and variability of the underlying anatomy and pathology. Researchers are continually developing new algorithms and techniques to improve the accuracy and reliability of feature extraction, with the ultimate goal of improving patient outcomes and advancing medical research.

One of the key features of CNNs is their ability to automatically learn and extract relevant features from image data, without the need for explicit feature engineering.

In CNNs, the feature extraction process is typically performed by a series of convolutional and pooling layers. The convolutional layers apply a set of learnable filters to the input image, which helps to identify different features and patterns in the image. The pooling layers then downsample the output of the convolutional layers, reducing the spatial resolution of the image while preserving its key features.

As the CNN learns to classify images, the filters in the convolutional layers adapt to become more effective at identifying relevant features for the task at hand. This process is often referred to as "feature learning", as the CNN is essentially learning to extract the most informative features from the image data.

One of the benefits of using CNNs for feature extraction is that they can automatically handle a wide range of image variations, such as changes in lighting conditions, viewpoint, and orientation. This makes them particularly useful for applications such as object recognition, where the same object may appear in different locations and orientations within an image.



(Deep Learning with Python 2^{nd} edition, François Chollet)