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Problem 1

1. Having the following information, reconstruct the main 2*2 matrix using back-propagation and explain the steps. The following table shows what number the sensor shows by beaming to the object at different angles and at different distances. Hint: We want to find the values of a 2*2 matrix object. For each angle, we should find which of the table's elements are involved in each distance.

angle	r = 0	r = 1	r = 2
0	10	7	-
45	7	8	2
90	12	5	-
135	5	9	3

2. Determine which one of the vessels in the reconstructed image T probably belonged to the bone and which one probably belonged to the air.
3. Why do you think this method cannot be used in practice to reconstruct T images?

1.1

To reconstruct the main 2x2 matrix using backpropagation, we need to analyze the given table and determine the values of the matrix elements. The table shows the numbers displayed by the sensor at different angles and distances.
Let's denote the matrix elements as follows:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

We can start by examining each row of the table:
For angle 0, the sensor shows 10 at r=0, 7 at r=1, and there is no value provided for r=2. From this, we can deduce that the element in the first row and first column (a) is 10, the element in the first row and second column (b) is 7, and the element in the second row and first column (c) is unknown.
For angle 45, the sensor shows 7 at r=0, 8 at r=1, and 2 at r=2. From this, we can deduce that the element in the first row and first column (a) is 7, the element in the first row and second column (b) is 8, and the element in the second row and first column (c) is 2.
For angle 90, the sensor shows 12 at r=0, 5 at r=1, and there is no value provided for r=2. From

this, we can deduce that the element in the first row and first column (a) is 12, the element in the first row and second column (b) is 5, and the element in the second row and first column (c) is unknown.
For angle 135, the sensor shows 5 at r=0, 9 at r=1, and 3 at r=2. From this, we can deduce that the element in the first row and first column (a) is 5, the element in the first row and second column (b) is 9, and the element in the second row and first column (c) is 3.
Therefore, the reconstructed 2x2 matrix is:

$$\begin{bmatrix} 10 & 7 \\ 2 & 3 \end{bmatrix}$$

1.2

In a CT image, the cells that correspond to bone and air have distinct characteristics that differentiate them from each other. Here are the key differences:

1. Density: Bone cells in a CT image have a higher density compared to air cells. This is because bone is a dense tissue composed of calcium and other minerals, while air is less dense.
2. Intensity: In a CT image, bone cells appear brighter or have higher intensity values compared to air cells. This is because the X-ray attenuation is higher in bone due to its density, resulting in a higher intensity signal in the image.
3. Texture and Structure: Bone cells in a CT image typically exhibit a more structured and well-defined appearance. They often have clear edges and show trabecular patterns or cortical structures. On the other hand, air cells appear as regions of lower density with less defined boundaries.
4. Hounsfield Units (HU): CT images use Hounsfield Units to measure the radiodensity of different tissues. Bone typically has HU values in the positive range, while air has negative HU values. This difference in HU values helps distinguish between bone and air cells.

Problem 2

1. How is contrast created between different tissues in MRI imaging?
2. The signal taken from the tissues is a damped sinusoidal function. How can the sinusoidal part be removed so that only the information related to the tissue remains?
3. The magnetic field created in the MRI imaging device is equal to the $B = 2.6+0.3z$ in the imaging at the cross-section $z = 2$. What frequency should we use and if the maximum signal that can be recorded by the device is $68 * 10^7 MHz$, find the fip ange. (Consider the gyroagneti coefficient of hydrogen equal to $42.5T/M$ and suppose that the number of hydrogen atoms in the target tissue is equal to 10^7)?

2.1

In MRI (Magnetic Resonance Imaging) imaging, contrast between different tissues is achieved through a combination of factors. These factors include:

1. **T1 Relaxation Time:** Tissues have varying T1 relaxation times, which represent the time taken for protons to realign with the magnetic field after being perturbed. Tissues with shorter T1 relaxation times appear brighter, while those with longer T1 relaxation times appear darker. The contrast between tissues can be enhanced by manipulating the timing of radiofrequency pulses and the delay between them, resulting in T1-weighted images.

2. **T2 Relaxation Time:** Tissues exhibit different T2 relaxation times, which indicate the time it takes for protons to lose coherence after being excited. Tissues with shorter T2 relaxation times appear darker, while those with longer T2 relaxation times appear brighter. T2-weighted images can be obtained by adjusting the echo time (TE) to emphasize tissue contrast based on T2 relaxation times.

3. **Proton Density:** Contrast can also be influenced by the concentration of protons in tissues, known as proton density. Tissues with higher proton density appear brighter, while those with lower proton density appear darker. Proton density-weighted images can be acquired to highlight this contrast.

4. **Contrast Agents:** Intravenous administration of contrast agents can further enhance tissue contrast. These agents modify the relaxation properties of tissues, resulting in increased contrast in specific areas of interest. Contrast agents are particularly useful in highlighting blood vessels, tumors, or areas of inflammation.

5. **Magnetic Field Strength:** The strength of the magnetic field used in MRI imaging can impact tissue contrast. Higher magnetic field strengths, such as 3 Tesla (3T) or 7 Tesla (7T), can improve the signal-to-noise ratio and enhance the visibility of subtle tissue differences.

2.2

To remove the sinusoidal part and retain only the information related to the tissue from a damped sinusoidal signal obtained from MRI tissues, a process called "signal demodulation" can be applied. Here's a general approach to achieve this:

1. **Fourier Transform:** Apply a Fourier transform to the damped sinusoidal signal. This converts the signal from the time domain to the frequency domain.

2. **Frequency Analysis:** Analyze the frequency spectrum obtained from the Fourier transform. The sinusoidal part of the signal is represented by a peak at a specific frequency.

3. **Filter Design:** Design a filter tailored to the characteristics of the damped sinusoidal signal and the desired frequency range for tissue information. The filter should have a passband that includes the frequencies of interest related to the tissue information while attenuating or rejecting the frequency corresponding to the sinusoidal component.

4. **Filter Application:** Apply the designed filter to the frequency spectrum. This effectively suppresses or eliminates the sinusoidal component, preserving the tissue-related information.

5. **Inverse Fourier Transform:** Perform an inverse Fourier transform on the filtered frequency spectrum to convert it back to the time domain. The resulting signal is the demodulated signal with the sinusoidal part removed.

It's important to note that the specific design and implementation of the filter depend on the characteristics of the damped sinusoidal signal and the desired frequency range for tissue information. Expertise in signal processing and familiarity with MRI techniques are recommended for accurate demodulation of the signal.

2.3

To find the frequency and flip angle, we can use the formula for the Larmor frequency and the maximum signal recorded by the device.
The Larmor frequency (ω) is given by the equation:

$$\omega = \gamma B$$

where γ is the gyromagnetic coefficient and B is the magnetic field strength.
Given that the gyromagnetic coefficient of hydrogen (γ) is $42.5\,\mathrm{T/M}$, and the magnetic field (B) at $z = 2$ is $2.6 + 0.3z$, we can substitute these values into the equation to find the frequency at $z = 2$:

$$B = 2.6 + 0.3z$$

$$B = 2.6 + 0.3(2)$$

$$B = 2.6 + 0.6$$

$$B = 3.2\,\mathrm{T}$$

$$\omega = \gamma B$$

$$\omega = 42.5 \times 3.2$$

$$\omega = 136\,\mathrm{MHz}$$

So, the frequency we should use is $136\,\mathrm{MHz}$.
Now, let's find the flip angle (θ). The flip angle is related to the maximum signal recorded by the device ($S_{\max}$) by the equation:

$$S_{\max} = \sin\left(\frac{\theta}{2}\right)$$

Given that $S_{\max}$ is $68 \times 10^7\,\mathrm{MHz}$, we can rearrange the equation to solve for the flip angle:

$$\theta = 2 \times \arcsin(S_{\max})$$

$$\theta = 2 \times \arcsin(68 \times 10^7)$$

$$\theta \approx 2 \times 1.5708$$

$$\theta \approx 3.1416\,\mathrm{radians}$$

Therefore, the flip angle is approximately 3.1416 radians.

Problem 3

In the figure below, we have three different materials with attenuations of μ_1, μ_2, and μ_3, the length of each of which is l_1, l_2, and l_3, respectively. If the input radiation is n_0, what is the value of n_3? and we have:

$$\mu_1(x) = 2x^2$$
$$\mu_2(x) = x + 3$$
$$\mu_3(x) = \frac{1}{x^2}$$

3.1

To find the value of N_3, we need to calculate the output ratio of μ_3 given the input radiation n_0, the attenuations μ_1, μ_2, and μ_3, and the lengths l_1, l_2, and l_3.
Let's start by calculating the output ratio N_1 of μ_1:

$$N_1 = n_0 \cdot e^{-\int_0^{l_1} \mu_1(x)\,dx}$$

Substituting the given attenuation $\mu_1(x) = 2x^2$:

$$N_1 = n_0 \cdot e^{-\int_0^{l_1} 2x^2\,dx}$$

Next, we calculate the output ratio N_2 of μ_2:

$$N_2 = N_1 \cdot e^{-\int_0^{l_2} \mu_2(x)\,dx}$$

Substituting the given attenuation $\mu_2(x) = x + 3$:

$$N_2 = N_1 \cdot e^{-\int_0^{l_2} (x+3)\,dx}$$

Finally, we calculate the output ratio N_3 of μ_3:

$$N_3 = N_2 \cdot e^{-\int_0^{l_3} \mu_3(x)\,dx}$$

Substituting the given attenuation $\mu_3(x) = \frac{1}{x^2+1}$:

$$N_3 = N_2 \cdot e^{-\int_0^{l_3} \frac{1}{x^2+1}\,dx}$$

Therefore we have:

$$N_3 = n_0 \cdot e^{-\int_0^{l_1} 2x^2\,dx} \cdot e^{-\int_0^{l_2} (x+3)\,dx} \cdot e^{-\int_0^{l_3} \frac{1}{x^2+1}\,dx}$$

Problem 4

Based on Artificial intelligence guided enhancement of digital PET: scans as fast as CT? paper, answer following questions:
1. What are the advantages of digital PET CT systems compared to previous systems?
2. Describe the idea and method used in the article, the description of the method should include the following:
1. What are network inputs and outputs?
2. What is the architecture of the network?
3. What are the evaluation criteria and results?

4.1

- Increased detector sensitivity: By utilizing silicon-photomultipliers (SiPM), digital PET/CT systems achieve higher detector sensitivity. This leads to improved spatial resolution and coincidence time resolution, resulting in enhanced image quality and better detection of small and low-count lesions.
- Improved signal recovery: The higher signal recovery of SiPM-based PET in digital systems enhances the detectability of lesions, particularly in low-count PET images reconstructed with the time-of-flight (TOF) option.
- Higher spatial and temporal resolution: Digital PET/CT systems offer improved time and spatial resolution, as well as better noise characteristics. This enables better image quality and more accurate detection of lesions.
- Reduction in acquisition time: Digital PET/CT systems allow for a reduction in acquisition time without significant loss of clinically relevant information. Studies have shown that acquisition times as short as 20 to 30 seconds per whole-body scan, comparable to a CT scan, are feasible. This reduction in acquisition time can improve patient comfort and workflow efficiency.
- Enhanced performance for lesion detection: Digital PET/CT systems have demonstrated improved performance in detecting lesions in oncology compared to previous systems. The combination of digital PET/CT technology and artificial intelligence-based image post-reconstruction techniques enables the generation of high-quality images from PET data acquired as quickly as CT scans.

In summary, digital PET/CT systems offer improved image quality, better lesion detection, and the potential for reduced acquisition times, making them a valuable advancement in PET imaging technology.

4.2

1. Network Inputs and Outputs: The study utilized a group of 2.5-dimensional (2.5D) images extracted from PET and CT scans as the network inputs. For each method (PET-only and PET/CT), a 3-channel image was generated, incorporating the previous and next slices. This approach aimed to provide additional anatomical information to the 2D network. The network's output was a synthetic full-dose PET image generated using an artificial neural network.
2. Network Architecture: The network architecture employed in the study was a modified version of the pix2pixHD deep-learning network, tailored to the specific requirements of the task. It consisted of a generator and a discriminator. The generator took an input image from the source domain (PET or PET/CT) and produced a corresponding image with the characteristics of the target domain (full-dose PET). The discriminator was responsible for distinguishing between real images and those generated by the generator. The pix2pixHD architecture utilized two generators operating at different resolutions to capture both local and global features, forming a "coarse-to-fine" generator. The discriminator was designed as a multi-scale network.

3. Evaluation Criteria and Results: The network's performance was evaluated using various criteria. Established metrics such as Structural Similarity Index Measure (SSIM), Peak Signal to Noise Ratio (PSNR), and SUV-based Mean Absolute Error (MAE) were employed to assess the similarity between the synthetic PET images and the ground truth full-dose PET images. These metrics were calculated on the test studies. Additionally, the network's performance was evaluated in terms of lesion detection and quantification by comparing the synthetic PET images to the ground truth images. The results demonstrated high visual image quality, with a mean absolute difference of 1.5 in lesion SUV max. The network achieved a patient-based sensitivity of 79% and a specificity of 100% for lesion detection.

Problem 6

In this question, we are going to learn about the challenges of using artificial intelligence and specifically deep learning in the analysis of medical images, according to this article
"Challenges of deep learning in medical image analysis – improving explainability and trust "
answer the following questions.
1. What is the impact of aversaria attacks on deep neural networks considering the noise of the images?
2. What are the challenges and solutions in creating a balanced and annotated database of medical images?
3. Why do we need visua explainability in addition to numerical measures of models? Give some examples of visua explainability algorithms.
4. Explain oe agnosti and oe speifi and compare in terms of advantages and disadvantages.

6.1

Addressing these challenges is crucial to ensure accurate and reliable results in healthcare applications. Adversarial attacks and noise in medical images can lead to biased and incorrect predictions, making it essential to develop effective denoising techniques. Researchers have explored various methods such as bilateral filtering, denoising autoencoders, and adversarial training using generative adversarial networks (GANs) to mitigate the impact of adversarial attacks and noise. By enhancing the robustness of deep neural networks, these techniques aim to improve the accuracy and reliability of medical image analysis.

6.2

The document discusses the challenges associated with creating a balanced and annotated database of medical images and proposes potential solutions. Here are the key points:
Challenges:

1. Scarcity of balanced annotated medical image data: The lack of large volumes of authentic annotated medical image data hinders the growth of deep learning in medical image diagnosis.

2. Imbalanced data: Data imbalance in the dataset can introduce bias in deep neural networks, leading to overfitted predictions and diagnoses.

Solutions:

1. Data augmentation: Researchers are using data augmentation techniques to generate synthetic datasets and compensate for the scarcity of medical image datasets. This approach involves manipulating the original dataset while preserving important features, effectively increasing the volume of the image dataset.

2. Collaboration with medical professionals: Involving medical experts in the image labeling and annotation process ensures accurate and reliable annotations.

3. Validation by medical practitioners: Thorough field-testing and assessment of deep learning models under the guidance of medical practitioners can validate AI-based computer-aided diagnostic systems, improving their performance and trustworthiness.

4. Sharing resources: Sharing research, tools, databases, and other resources within the community can help address the challenge of unavailability of annotated medical image data.

These solutions aim to overcome the challenges of creating a balanced and annotated database of medical images, enabling the training and validation of robust deep learning architectures in medical image analysis.

6.3

- Reasons for Visual Explainability:

    1. Enhanced user understanding: Visual explanations are more informative and captivating to users compared to numerical quantifiers. They provide an intuitive and comprehensible representation of how the model arrives at its predictions.
    2. Societal acceptance: To gain trust and acceptance from society, visual explainability must be actively incorporated into computer-aided diagnostic (CAD) systems. Society is more likely to embrace AI when they can visually grasp the decision-making process.

- Examples of Visual Explainability Algorithms:

    1. Local Interpretable-Model Agnostic Explainer (LIME): LIME is a method employed to explain image classification tasks using convolutional neural networks (CNNs). It generates explanations by highlighting the pixels in an image that are responsible for a specific prediction, making it logically understandable by humans.
    2. Gradient-based Class Activation Maps (Grad-CAMs): Grad-CAMs are tailored to visual data-based architectures like CNNs. They generate gradient maps that describe the pixels in an image contributing to a particular prediction. This aids in localizing infected regions in medical images and understanding the extent of diseases.

3. Class Activation Maps (CAMs): CAMs are another technique used to explain image classification tasks using CNNs. They provide visual explanations by highlighting the regions in an image that are crucial for a specific prediction.
4. Deconvolution techniques: Deconvolution techniques are employed to explain deep learning models by visualizing the features learned by the model. They facilitate understanding of the patterns and representations captured by the model.

These visual explainability algorithms offer insights into the decision-making process of deep learning models, rendering them more transparent and interpretable for users and stakeholders.

6.4

The document discusses the benefits of model agnostic explainability methods in the context of deep learning in medical image analysis. Model agnostic methods are described as providing a high level of flexibility and being able to produce satisfactory results for different types of AI architectures and algorithms. These methods are also mentioned as being able to explain a wide spectrum of deep learning models.
On the other hand, the document mentions model specific explainability methods, such as GradCAM, which are specific to visual data-based architectures like CNNs. These methods provide more specific explanations than their model agnostic counterparts, but they may not be applicable to a wide range of deep learning models.
Based on this information, it can be inferred that model agnostic approaches offer flexibility and can be applied to a wide range of models, while model specific approaches may provide more specific explanations but are limited to certain types of models.