**Development of machine vision algorithms for radiomics: novel approach to segment tumor tissue and dose for particle therapy**

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**CHAPTER 1: Tomography methods for medical imaging**

1. Inverse problem

The inverse problem in tomography reconstruction is a fundamental challenge in medical imaging. It involves recovering the internal structure of an object from a set of its projections or measurements

Key points:

* Definition: The process of reconstructing an image from its projections, which is the opposite of the forward problem (creating projections from an image)
* Ill-posed nature: The inverse problem is often ill-posed, meaning small errors in measurements can lead to large errors in the reconstruction
* Regularization: Techniques like Tikhonov regularization are used to stabilize the solution and handle noise in the data
* Iterative methods: Algorithms such as ART (Algebraic Reconstruction Technique) and SIRT (Simultaneous Iterative Reconstruction Technique) are commonly used to solve the inverse problem
* Understanding and addressing the inverse problem is crucial for developing accurate and robust reconstruction algorithms in medical imaging modalities like CT and SPECT.
1. Radon and Fourier Transforms

The Radon and Fourier transforms are fundamental mathematical tools in tomographic imaging:

* **Radon Transform:** Maps a function in 2D space to a set of line integrals. In CT, it represents the X-ray attenuation along different paths through the object.
* **Fourier Transform:** Converts spatial domain information to frequency domain. It's crucial in image processing and reconstruction algorithms.
* **Fourier Slice Theorem:** Connects the Radon and Fourier transforms, stating that the 1D Fourier transform of a projection is equivalent to a slice of the 2D Fourier transform of the original image.
* **Applications:** These transforms are essential in CT image reconstruction, allowing the conversion of projection data into cross-sectional images.
* Understanding these transforms is crucial for developing and optimizing reconstruction algorithms in medical imaging, particularly in CT and SPECT modalities.
1. CT

Computed Tomography (CT) is a widely used medical imaging technique that creates detailed cross-sectional images of the body

Key points:

* X-ray attenuation: CT measures the absorption of X-rays as they pass through different tissues
* Multiple projections: The X-ray source rotates around the patient, capturing images from various angles
* Image reconstruction: Advanced algorithms process the collected data to create 3D images
* CT reconstruction algorithms:
* Filtered Back Projection (FBP): A traditional method that's fast but can produce artifacts
* Iterative Reconstruction (IR): More advanced technique that reduces noise and improves image quality
* Model-based Iterative Reconstruction (MBIR): Incorporates physical models of the imaging system for enhanced accuracy
* Applications of CT in medical imaging:
* Diagnostic imaging for various conditions, including cancer, cardiovascular diseases, and trauma
* Image-guided interventions and surgical planning
* 3D visualization of complex anatomical structures

 4. SPECT (Single Photon Emission Computed Tomography)

SPECT is a nuclear medicine imaging technique that provides three-dimensional functional images of organs and tissues.

Key points:

* Principle: Uses gamma-emitting radioisotopes and rotating gamma cameras to detect emitted photons
* Image acquisition: Multiple 2D projections are taken around the patient
* Reconstruction: Tomographic images are created using algorithms like those in CT
* Applications: Widely used in cardiac, brain, and bone imaging
* SPECT reconstruction algorithms typically involve:
* Filtered Back Projection (FBP): Traditional method, fast but prone to noise
* Iterative reconstruction: Methods like OSEM (Ordered Subset Expectation Maximization) that improve image quality
* Attenuation and scatter correction: Techniques to account for photon interactions within the body

Recent advancements in SPECT include the development of CZT detectors for improved energy resolution and sensitivity, and the integration of CT for hybrid SPECT/CT imaging.

**CHAPTER 2: Particle therapy**

1. General introduction
2. BNCT

Boron Neutron Capture Therapy (BNCT) is an innovative and highly targeted form of radiotherapy that holds significant promise in the treatment of various cancers, particularly those that are difficult to treat with conventional methods. This advanced technique combines principles of nuclear physics, radiobiology, and cancer therapeutics to deliver a precise and potent treatment to cancer cells while minimizing damage to healthy tissues.

The fundamental principle of BNCT lies in its two-step approach:

1. Boron Delivery: A boron-10 containing compound is selectively delivered to tumor cells. This compound is designed to accumulate preferentially in cancer cells due to their altered metabolism and increased uptake rates.
2. Neutron Irradiation: Once the boron compound has concentrated in the tumor, the patient is exposed to a beam of low-energy (thermal) neutrons. These neutrons interact with the boron-10 atoms, initiating a nuclear reaction.

The nuclear reaction that occurs is the core of BNCT's effectiveness:

¹⁰B + ¹n → ⁷Li + ⁴He + 2.79 MeV

This reaction produces high-energy alpha particles (⁴He) and lithium nuclei (⁷Li). These particles have a very short range in tissue (5-9 μm), which is approximately the diameter of a single cell. This limited range ensures that the destructive energy is confined primarily to boron-containing cells, providing a highly localized and targeted treatment.

The efficacy of BNCT depends on several critical factors:

* Boron Delivery Agents: The development of boron compounds that can selectively accumulate in tumor cells is crucial. Current research focuses on boronophenylalanine (BPA) and sodium borocaptate (BSH), among others.
* Neutron Source: The quality and intensity of the neutron beam are vital. Historically, nuclear reactors were used, but accelerator-based neutron sources are becoming more prevalent due to their practicality in clinical settings.
* Dosimetry: Accurate measurement and calculation of the radiation dose delivered to tumor and healthy tissues are essential for treatment planning and evaluation.
* Tumor Biology: Understanding the biological characteristics of different tumor types is crucial for optimizing boron delivery and treatment efficacy.

BNCT offers several potential advantages over conventional radiotherapy:

* High Selectivity: The localized nature of the nuclear reaction allows for precise targeting of tumor cells.
* Reduced Side Effects: The short range of the reaction products minimizes damage to surrounding healthy tissues.
* Potential for Treating Deep-Seated Tumors: The penetrating nature of neutrons allows for the treatment of tumors that may be inaccessible to conventional radiotherapy.
* Single-Session Treatment: In many cases, BNCT can be administered in a single session, reducing the need for multiple hospital visits.

Despite these advantages, BNCT faces several challenges:

* Complex Infrastructure: The need for specialized neutron sources and facilities limits widespread adoption.
* Boron Delivery Optimization: Ensuring sufficient and selective accumulation of boron in tumor cells remains a significant research focus.
* Treatment Planning: The complex physics and radiobiology of BNCT require sophisticated treatment planning systems.

Current research in BNCT is multifaceted, focusing on:

* Developing new boron delivery agents with improved tumor selectivity and retention.
* Advancing accelerator technology for more efficient and compact neutron sources.
* Enhancing imaging techniques for real-time monitoring of boron distribution and neutron flux.
* Exploring combination therapies that could synergize with BNCT.

BNCT has shown promising results in treating various cancers, including glioblastoma multiforme, recurrent head and neck cancers, and malignant melanomas. As research progresses and clinical trials expand, BNCT has the potential to become a valuable addition to the arsenal of cancer treatments, offering hope for patients with otherwise difficult-to-treat malignancies.

The future of BNCT lies in its continued refinement and integration into mainstream cancer care. As our understanding of cancer biology deepens and technology advances, BNCT stands poised to play an increasingly important role in the fight against cancer, embodying the principles of precision medicine and targeted therapy.

**CHAPTER 3: Deep learning methods: basic concepts**

Deep learning is a subset of machine learning that uses artificial neural networks with multiple layers to learn and represent complex patterns in data. These deep neural networks are capable of automatically learning hierarchical features from raw input, making them particularly effective for tasks involving high-dimensional data such as images, speech, and text.

Key points:

* Hierarchical feature learning: Each layer in the network learns increasingly abstract representations of the input data.
* End-to-end learning: Deep learning models can learn directly from raw input to final output, often eliminating the need for manual feature engineering.
* Scalability: Performance typically improves with more data and larger models, making deep learning well-suited for big data applications.
* Transfer learning: Knowledge gained from one task can often be applied to related tasks, improving efficiency and performance.

Among the various deep learning architectures, Convolutional Neural Networks (CNNs) have emerged as a powerful tool, particularly in the domain of image analysis and computer vision. CNNs are designed to automatically and adaptively learn spatial hierarchies of features from input images.

The key components of a CNN include:

1. Convolutional layers: These layers apply learnable filters to the input, creating feature maps that highlight important patterns.
2. Pooling layers: These reduce the spatial dimensions of the feature maps, providing a form of translational invariance.
3. Fully connected layers: These layers typically appear at the end of the network and perform high-level reasoning.
4. Activation functions: Non-linear functions like ReLU that introduce non-linearity into the network, allowing it to learn complex patterns.

CNNs have several advantages that make them particularly suited for image analysis tasks:

* Parameter sharing: Convolutional filters are applied across the entire image, significantly reducing the number of parameters compared to fully connected networks.
* Spatial locality: CNNs can effectively capture local patterns and spatial relationships in images.
* Hierarchical feature learning: Deeper layers in the network can learn increasingly complex and abstract features.
* Translation invariance: The use of pooling layers helps the network recognize patterns regardless of their position in the image.

In medical imaging, CNNs have revolutionized various tasks including image classification, segmentation, and object detection. They have shown remarkable performance in analyzing complex medical images such as CT scans, MRIs, and X-rays, often achieving accuracy comparable to or exceeding that of human experts.

As research in deep learning and CNNs continues to advance, we can expect further improvements in model architectures, training techniques, and applications, particularly in specialized fields like medical imaging and radiomics.

**CHAPTER 4: Development of machine vision algorithms for medical images**

Another important aspect to consider in image segmentation using deep learning is the choice of network architecture. Convolutional Neural Networks (CNNs) have shown remarkable performance in various image analysis tasks, including segmentation. However, the specific architecture design can greatly impact the model's effectiveness and efficiency. For instance, U-Net and its variants have become popular choices for medical image segmentation due to their ability to capture both local and global features.

 1. UNet

 2. MSCA multi-scale channel attention network

 3. MDAG multi dimension attention gate network

 4. SRSNetwork strongly representative semantic-guided network

* 2D over 2.5D analysis: overfitting problems
* 3D models
* CenterNet stage
* Exploring the use of a neural network to find the center of the image

Another promising approach is two classify images divided into small cubes. Classification task is simpler than segmentation. The model could be a 3D UNet:

* Database divided by cubes
* Balance with random centers
* 3D UNet classification
* Use training data for segmentation

One promising approach in image analysis is using a neural network to identify the center of an image. This technique can be particularly useful in medical imaging for tasks such as tumor localization or organ centering. Here are some key points to consider:

* Convolutional Neural Networks (CNNs) can be trained to predict the coordinates of the image center
* This approach can be combined with attention mechanisms to focus on relevant features
* Potential applications include automatic ROI (Region of Interest) detection and improved image registration
* Challenges may include dealing with varying image sizes and ensuring robustness across different imaging modalities

Implementing such a network could significantly enhance the preprocessing stage of medical image analysis, potentially improving the accuracy of subsequent segmentation or classification tasks.

* Radiomics data ???

**CHAPTER 5: SPECT reconstruction algorithm in innovative neutron therapy**

1. MC studies: Neutron production, imaging production
2. Monte Carlo simulation for neutron production and transport

Monte Carlo (MC) algorithms are computational methods that use repeated random sampling to obtain numerical results. In the context of neutron production and transport, MC simulations are invaluable tools for modeling complex physical processes.

The Monte Carlo method for neutron simulation typically involves:

* Generating individual neutrons with initial positions, directions, and energies based on the source characteristics
* Tracking each neutron's path through the simulated environment, considering interactions with materials
* Using probability distributions to determine outcomes of neutron interactions (e.g., scattering, absorption, or fission)
* Recording relevant data such as energy deposition, neutron flux, or detector responses

For neutron production simulation, MC methods can model various neutron sources, including accelerator-based sources, nuclear reactors, and spontaneous fission sources. These simulations help in optimizing neutron yield, energy spectrum, and spatial distribution for applications like BNCT or neutron imaging.

Key advantages of MC simulations in neutron studies include:

* Ability to model complex geometries and material compositions
* Accurate representation of neutron transport physics
* Flexibility in scoring various quantities of interest
* Capability to simulate rare events that might be difficult or expensive to measure experimentally

Popular MC codes for neutron simulations include MCNP, Geant4, and FLUKA, each offering specific features for different applications in nuclear physics and radiation transport.

1. Test bench validation
2. Tomography by iterative approach
3. Iterative reconstruction for SPECT tomography using 478 keV gamma rays

Iterative reconstruction methods are powerful techniques used in Single Photon Emission Computed Tomography (SPECT) to produce high-quality images from gamma-ray emissions. For the specific case of 478 keV gamma rays, which are relevant in certain nuclear medicine procedures, the iterative approach offers several advantages:

* Improved image quality: Iterative methods can better handle the noise and artifacts associated with high-energy gamma rays.
* Accurate modeling: These techniques can incorporate detailed physics models of gamma-ray interactions and detector responses.
* Flexibility: Iterative methods allow for the inclusion of prior information and constraints, which can be particularly useful when dealing with the specific challenges of 478 keV emissions.

The general process of iterative reconstruction for SPECT with 478 keV gamma rays involves:

1. Initial estimate: Start with an initial guess of the activity distribution.
2. Forward projection: Simulate the expected projection data based on the current estimate.
3. Comparison: Compare the simulated projections with the actual measured data.
4. Back projection: Update the current estimate based on the differences observed.
5. Iteration: Repeat steps 2-4 until convergence or a predefined number of iterations.

Common iterative algorithms used in SPECT reconstruction include Maximum Likelihood Expectation Maximization (MLEM) and Ordered Subset Expectation Maximization (OSEM). These methods can be adapted to handle the specific characteristics of 478 keV gamma rays, such as increased scatter and attenuation in tissue.

When applying iterative reconstruction to 478 keV SPECT imaging, special considerations may include:

* Enhanced scatter correction techniques to account for the higher likelihood of Compton scattering at this energy level.
* Robust attenuation correction methods to compensate for the increased attenuation of higher energy gamma rays in tissue.
* Optimization of the number of iterations and subsets (in OSEM) to balance image quality and noise characteristics specific to 478 keV emissions.

By carefully implementing these iterative reconstruction techniques, it's possible to achieve high-quality SPECT images from 478 keV gamma rays, potentially improving diagnostic accuracy and quantitative analysis in nuclear medicine procedures that utilize this specific energy.

Deep Learning Approach for SPECT Image Reconstruction

1. **Deep Learning (DL)** has emerged as a promising approach for SPECT image reconstruction, offering several potential advantages over traditional methods:
2. **End-to-end Learning:** DL models can learn to map raw projection data directly to reconstructed images, potentially capturing complex patterns and relationships that may be missed by conventional algorithms.
3. **Noise Reduction:** Deep neural networks can be trained to effectively suppress noise while preserving important image features, potentially improving image quality and diagnostic accuracy.
4. **Faster Reconstruction:** Once trained, DL models can perform reconstructions much faster than iterative methods, which could be particularly beneficial in clinical settings.
5. **Incorporation of Prior Knowledge:** DL architectures can be designed to incorporate anatomical priors or other domain-specific knowledge, potentially leading to more accurate reconstructions.
6. Several DL architectures have been explored for SPECT reconstruction, including:
7. **Convolutional Neural Networks (CNNs):** Used for learning the mapping between sinograms and reconstructed images.
8. **Generative Adversarial Networks (GANs):** Employed to generate high-quality SPECT images from low-dose or limited-angle acquisitions.
9. **Unrolled Networks:** These architectures mimic iterative reconstruction algorithms but with learnable parameters, combining the strengths of model-based and data-driven approaches.
10. While DL approaches show great promise, challenges remain, including the need for large training datasets, concerns about generalization to unseen data, and the "black box" nature of deep neural networks. Ongoing research is focused on addressing these challenges and validating DL-based reconstruction methods for clinical use in SPECT imaging.

**CHAPTER 6: CT segmentation also on BNCT framework**

Computed Tomography (CT) segmentation of organs plays a crucial role in improving SPECT reconstruction, particularly in the context of BNCT (Boron Neutron Capture Therapy). This process involves accurately delineating different organs and tissues from CT images, which can then be used to enhance the quality and accuracy of SPECT reconstructions.

Here's how CT segmentation contributes to improved SPECT reconstruction:

* **Attenuation Correction:** CT-based organ segmentation provides detailed attenuation maps, allowing for more accurate correction of gamma-ray attenuation in SPECT images. This is especially important for deep-seated organs or in patients with varying tissue densities.
* **Scatter Correction:** Organ-specific segmentation enables more precise modeling of scatter contributions from different tissues, leading to improved scatter correction in SPECT reconstructions.
* **Anatomical Priors:** Segmented CT images can be used as anatomical priors in iterative reconstruction algorithms, guiding the SPECT reconstruction process and potentially reducing noise and artifacts.
* **Partial Volume Correction:** Accurate organ segmentation allows for better estimation and correction of partial volume effects, which can significantly impact quantitative SPECT measurements.
* **Region-Specific Reconstruction:** With precise organ segmentation, reconstruction parameters can be optimized for specific regions of interest, potentially improving resolution and contrast in critical areas.

In the context of BNCT, accurate CT segmentation is particularly important for:

* **Treatment Planning:** Precise delineation of tumor and healthy tissues is crucial for optimizing boron delivery and neutron irradiation.
* **Dose Calculation:** Organ segmentation enables more accurate estimation of radiation dose distribution to both target and healthy tissues.
* **Treatment Monitoring:** Improved SPECT reconstruction through CT segmentation allows for better assessment of boron uptake and distribution before and during BNCT.

Advanced machine learning techniques, particularly deep learning models like U-Net and its variants, have shown promising results in automating and improving the accuracy of CT organ segmentation. These methods can potentially enhance the overall workflow and effectiveness of BNCT by providing more reliable anatomical information for SPECT reconstruction and subsequent treatment planning.