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Multimodal Imaging in Oncology: Challenges and Future Directions

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Abstract: Multimodal imaging, a vital tool in oncology, combines various imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) to offer valuable insights for tumor detection, diagnosis, staging, and treatment planning. Despite its advantages, challenges persist in image registration, fusion, optimization of algorithms, hardware advancements, and the integration of artificial intelligence (AI) and computer vision techniques. This paper delves into the current state of multimodal imaging in oncology, addresses the challenges faced, explores potential solutions, and underscores future developments to augment diagnostic and therapeutic capacities, including the application of AI, computer vision, and big data analytics to enhance the efficiency and effectiveness of multimodal imaging in cancer diagnosis and treatment. Additionally, it highlights how AI-powered algorithms can automate image analysis, assist in tumor segmentation, and provide predictive insights, ultimately improving the precision and speed of diagnosis and treatment planning in oncology.

Keywords: Multimodal imaging, Oncology, Computed tomography, Magnetic resonance imaging, Positron emission tomography, Image Guided Radiation Therapy, Stereotactic Body Radiation Therapy, image registration, Fusion, Algorithm optimization, Hardware advancements, Computer vision; Artificial intelligence (AI).

1. Inctroduction

Multimodal imaging integrates data from various imaging methods, such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET), to generate a thorough depiction of a tumor's anatomical and functional traits [1].[2] explores the intersection of mechanical engineering and computer science to enhance logistics automation. Conducted at Dortmund University of Technology, it focuses on precise robot control through accurate positional information.This approach has gained widespread acceptance in oncology due to its capacity to deliver more precise and comprehensive information than single imaging modalities [3]. However, several hurdles remain in the application of multimodal imaging, including complications in image registration and fusion, respiratory motion artifacts, and the necessity for improved algorithms and hardware advancements [4].

In recent years, Image Guided Radiation Therapy (IGRT) and Stereotactic Body Radiation Therapy (SBRT) have emerged as the primary development directions of photon radiotherapy equipment. The accurate IGRT and large-fraction high-dose technology in SBRT demand that the imaging and positioning accuracy of medical imaging equipment reach the submillimeter level, a challenge for traditional single-modal imaging technology. Multimodal imaging technology arose to meet this need, combining structural imaging such as CT and MRI with functional imaging techniques like PET and Single-Photon Emission Computed Tomography (SPECT). This approach offers a more comprehensive and precise understanding of the human body's internal structure, function, and molecular levels. Multimodal imaging holds promising applications in pre-radiotherapy staging diagnosis and whole-body screening, radiotherapy planning, tumor localization, radiotherapy execution, and post-radiotherapy outcome assessment.

In the late 2010s, research at CERN (European Organization for Nuclear Research) and in China focused on the components and applications of accelerators, including S-band and X-band. P Wang and Z Wang [5] proposed an RF system based on two klystrons and demonstrated its utility with two methods. They also developed and tested the spherical pulse compressor for the S-band high-power test stand at Tsinghua. A correction cavity chain for CLIC was designed and tested as well. For X-band accelerators, a pulse compressor and a compact RF rotary joint were designed, fabricated, and tested. Additionally, original accelerating structures such as half-cell and in-depth physics research based on accelerators were conducted. Z Wang's [6] research on X-ray targets aimed to explore damage behaviors and dose performance under high-frequency electron beam shock.

2. Multimodal Imaging Techniques in Oncology

Computed Tomography (CT) imaging technology, which was introduced in the 1970s, has revolutionized medical imaging and diagnosis. CT imaging utilizes X-rays, γ-rays, ultrasound, and other imaging modalities to create a complete image by angle scanning and receiving transmitted rays using a highly sensitive instrument [7]. CT imaging offers a fast imaging speed, high spatial resolution, and the ability to distinguish tissues of different densities, providing accurate anatomical information [7]. However, CT imaging has some limitations, including insufficient differentiation of soft tissues and inadequate sensitivity, which can increase the exposure to ionizing radiation [8]. Figure 1 and Figure 2 illustrate the schematic diagram and imaging example of CT imaging, respectively.

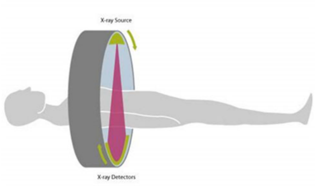

Figure 1. Schematic diagram of CT imaging principle.

Figure 2. CT imaging example.

Computed Tomography (CT) was introduced in the 1970s. It can use X-rays, γ-rays, ultrasound, etc. Angle scanning, using a highly sensitive instrument to receive the transmitted rays and reconstruct a complete image. The imaging speed is fast (second level), the spatial resolution is high (submillimeter), and it can distinguish tissues of different densities very well, and can provide accurate anatomical information. Its disadvantages are insufficient differentiation of soft tissues and insufficient sensitivity, which will bring additional doses of ionizing radiation to the human body. Figure 1 and Figure 2 are the schematic diagram and imaging example of CT imaging, respectively.

Magnetic Resonance Imaging (MRI) began to be applied on a large scale in the 1980s, using the Zeeman splitting of hydrogen nuclei under an external magnetic field, using pulsed radio frequency signals for nuclear resonance excitation, and passing through the signal emitted when the energy level retreats Determine the density of hydrogen atoms. MRI has high spatial resolution (1-2 mm), very good soft tissue imaging, and no ionizing radiation dose. The development and application of MRI functional imaging sequences such as Dynamic Contrast Enhanced Magnetic Resonance Imaging (DCE-MRI) and Blood Oxygen Dependent (BOLD) have made MRI able to realize multi-sequence and multi-parameter imaging, and comprehensively provide body information from anatomical, functional and even molecular perspectives.

Single Photon Emission CT (SPECT) and Positron Emission Tomography (PET) came out in the 1990s. According to the difference between diseased tissue and normal tissue metabolism, radioactive tracking drugs are used to locate radioactive drugs through detectors to find diseased tissues. It is characterized by functional imaging, which can provide metabolic information, has high sensitivity, and can perform whole-body imaging without depth limitations, but has poor spatial resolution (5-10 mm) and slow imaging. The radiopharmaceuticals for SPECT contain Tc99, and the gamma-ray detector emitting at 141keV has a collimator to ensure orientation through the beam direction. PET radiopharmaceuticals usually contain F18 positron annihilation emitting 511keV gamma rays that can be localized by the time difference between the two detector signals. In recent years, with the development of molecular biology, biochemistry and other disciplines, more radioactive tracers with superior performance have been applied to clinics. Combined with anatomical imaging, radiopharmaceutical-labeled genes can even achieve gene imaging, providing a deeper level of Information such as molecular metabolism has broad prospects in early diagnosis of diseases and research on disease mechanisms.

3. Development and Application

Multimodal imaging has been widely used in clinical practice to improve the accuracy of diagnosis and treatment planning. For instance, CT/PET and PET/MRI have been shown to be effective in cancer imaging, providing complementary information about tumor metabolism and anatomy [9-11]. In addition, CT/MRI has been used to diagnose and monitor musculoskeletal disorders, such as osteoarthritis and spinal cord injury [12]. [13] employs Xception model and data augmentation for automated quality inspection of casting product images, improving accuracy and efficiency Moreover, CT/SPECT has been used to evaluate bone mineral density and diagnose bone diseases, such as osteoporosis and bone tumors [14,15].

Commonly used multimodal imaging includes CT/PET, CT/SPECT, CT/MRI, and PET/MR that have appeared in recent years. Early multimodal imaging used different imaging devices to image sequentially. Images are acquired at different times and in different patient positions, with different spatial resolutions and pixel sizes. [16] examines user preference analysis for smartphones and apps, highlighting the importance of methods based on entity similarity and semantic assessment to gauge user satisfaction. During image acquisition, changes in heartbeat, respiration, blood sugar index, etc. lead to organ movement, changes in the position of tumors and surrounding normal tissues, and even The change of breathing pattern changes the movement pattern of the tumor, which brings great difficulties to image registration and fusion. In the 1990s, CT/PET, CT/SPECT all-in-one machines appeared, which realized imaging in the same body position on the same machine, simplified the image registration process, reduced the workload of image fusion, and increased the reliability of fused images.

3.1. CT/PET and CT/SPECT

PET/CT is a powerful diagnostic tool that combines the functional information from PET with the anatomical details provided by CT, enabling more accurate tumor localization and staging [17]. PET/CT has been widely used in oncology for the detection and characterization of various cancers, including lung, breast, and colorectal cancers [18].

The schematic diagram of the CT/PET all-in-one machine is shown in Figure 5. Although PET/SPECT can provide biological and biochemical information such as the metabolism of the target area from the molecular level, and observe the metabolic abnormalities in the lesion before the morphological abnormalities appear, but due to its low spatial resolution (5mm), it cannot accurately detect tumors. position. Combined with CT with higher spatial resolution, it can improve the spatial resolution and accurately locate the tumor. At the same time, it can reduce false positive or false negative misdiagnosis caused by PET/SPECT or CT single modality imaging. In addition, since the X-ray pairs emitted by radioactive missing drugs will be absorbed or scattered by human tissues, the brightness will decrease accordingly. Due to the good penetration performance of CT, PET/SPECT images are attenuated and corrected, which greatly improves the image quality and improves imaging quality. speed. Figure 6 shows PET images before and after CT attenuation correction. The fused images of CT/PET and CT/SPECT can provide accurate anatomical and functional information. It is mainly used in tumor staging, diagnosis, radiotherapy plan formulation, and effect evaluation after radiotherapy.

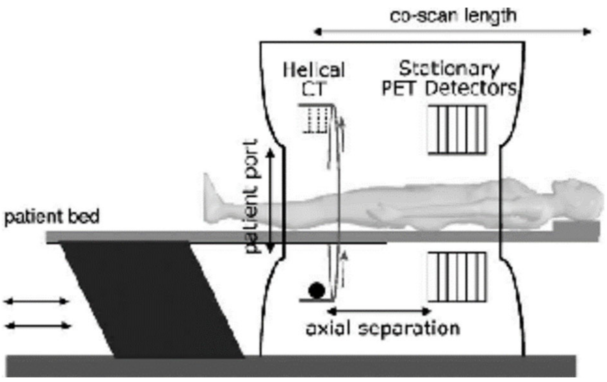

Figure 5. Schematic diagram of CT/PET integrated machine.

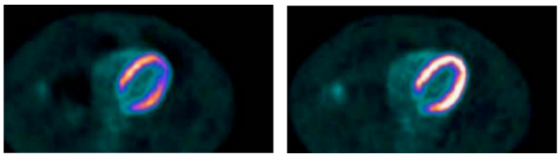

Figure 6. CT/PET image attenuation correction (A before correction, B after correction).

3.2. PET/MRI

PET/MRI is a relatively new hybrid imaging modality that combines the functional information from PET with the high soft-tissue contrast provided by MRI [19]. This modality has shown promise in the assessment of various cancers, such as prostate, brain, and gynecological malignancies, and offers potential advantages over PET/CT in terms of reduced radiation exposure and improved soft-tissue visualization [20].

PET/MRI multi-modal imaging technology combines MRI's good spatial resolution, soft tissue contrast ability, and functional sequence with PET's high sensitivity and specificity of functional imaging to comprehensively provide tumors and surrounding normal tumors from the aspects of morphology, function, and molecules. Biochemical information of the tissue. MRI structural imaging can perform attenuation correction on PET images and improve the quality of PET images. PET/MRI can also realize simultaneous acquisition of images at the same time and at the same place. The difficulty of image registration and fusion is greatly reduced, and the image quality is improved. The functional sequence of MRI can supplement the molecular information of PET, and comprehensively and accurately describe the metabolism of the target area from multiple perspectives. The PET/MRI image fusion is shown in Fig. 7. In addition, PET/MRI imaging greatly reduces the ionizing radiation dose to the human body.

The technical difficulty of the PET/MRI all-in-one machine lies in the influence of the MRI magnetic field on the PET photomultiplier tube. The Siemens Biograph mMR system is the world's first full-body PET/MR imaging system that realizes simultaneous data acquisition. The PET/MR all-in-one machine uses a new type of photoelectric converter The avalanche diode and the new detection crystal form the detector part, and after a series of electromagnetic shielding treatments, the detector part is embedded in the MR magnet cavity, realizing the integration and synchronous acquisition of PET and MR. Schematic diagrams of the PET/MRI all-in-one machine are shown in Figures 8 and 9.

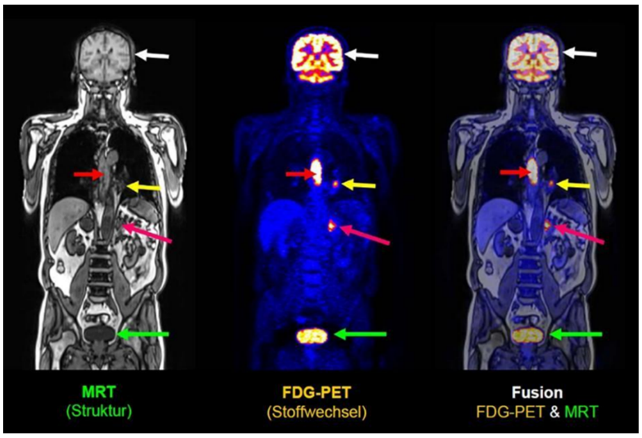

Image 7: PET/MRI integrated machine image fusion

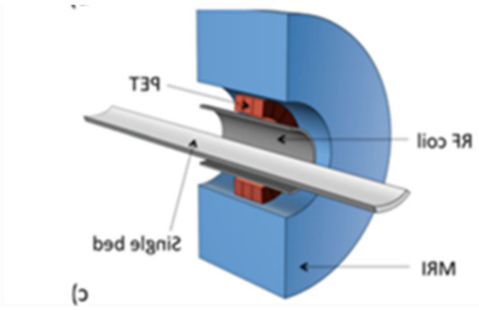

Figure 8: Schematic diagram of PET/MRI integrated machine 1

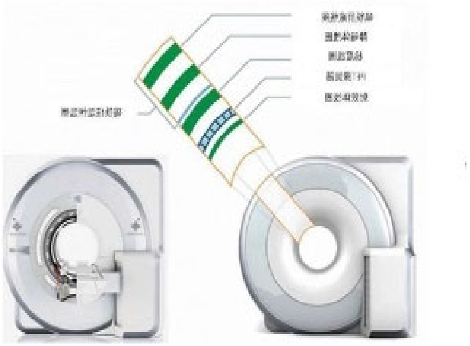

Figure 9: Schematic diagram of PET/MR integrated machine 2.

3.3. Application of Multimodal in Target Delineation

The common means of target delineation include manual delineation and threshold delineation. Manual delineation, as a commonly used method of target volume delineation in clinical practice, refers to the artificial identification of physiological causes of anatomical abnormalities that lead to differences in radiopharmaceutical absorption. This method relies on the expertise and experience of physicists, is affected by physicist fatigue, observation random errors, and requires the cooperation of experts in multiple fields. The threshold delineation method refers to setting the threshold of radiopharmaceutical absorption and automatically delineating the target area. This method ignores the heterogeneity within the tumor and the influence of motion artifacts, and it is difficult to determine the threshold value clinically, and there are large errors.

The delineation of the target area supported by multimodal imaging technologies such as PET/CT is shown in Figure 10. First, the patient remains still in the treatment position, and the FDG-PET-CT fusion image is obtained. As shown in Figure A, the lymph node metastases (green line) and the naked eye target area of the primary tumor (yellow line) were manually marked in the contrast-enhanced CT image, and the metabolically active area shown by the radioactive missing drug in the PET image was automatically marked in the fused image, as shown in Figure B. Considering the tumor movement and random error, the macroscopic target area was appropriately enlarged, and the treatment plan was further formulated. As shown in Figure 10.

Surveys show that multimodal imaging techniques such as PET/CT can significantly reduce the randomness of target volume delineation and reduce the interference caused by human factors; however, there is currently not enough evidence to prove that the cure rate of cancer radiotherapy can be improved as a result. The factors are too few samples and insufficient imaging precision.

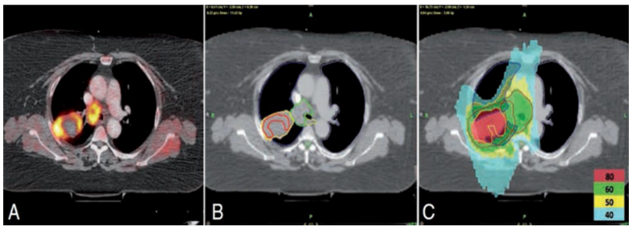

Figure 10. Target delineation for PET/CT multimodal imaging.

4. Challenges and Future Development of Multimodal Technology

One of the main challenges in multimodal imaging is the accurate registration and fusion of images from different modalities [19]. Various factors can affect the quality of image registration, such as differences in patient positioning, scanner calibration, and image resolution [3]. These factors can lead to misalignment between the images and potentially inaccurate diagnosis or treatment planning [4].

Respiratory motion artifacts are a common issue in multimodal imaging, particularly in thoracic and abdominal regions [17]. These artifacts can result in image degradation, inaccurate tumor localization, and overestimation of the target volume, potentially affecting the quality of diagnosis and treatment planning [18].

4.1. Image Registration Accuracy

The different timeliness of imaging in different modalities changes the position of the tumor and its surrounding normal tissues, and even changes the movement mode of the tumor. Images are obtained by different devices at different locations, and the spatial coordinate systems are inconsistent, and image registration involves coordinate system conversion. The non-rigid transformations involved in image registration between different modalities, which typically occur in somatic tumors, further increase the difficulty of image registration. The above factors increase the difficulty of image registration and affect the registration accuracy.

The development direction to improve the accuracy of image registration is to use an all-in-one machine to avoid non-rigid transformation of the image as much as possible, so that the imaging is in the same coordinate system as much as possible. Introduce additional markers as registration reference points, and use neural network, computer deep learning and other methods to improve image registration algorithms to increase registration accuracy.

4.2. Image fusion strategy

Image fusion includes three levels of pixel-level fusion, feature-level fusion, and decision-level fusion. The currently commonly used algorithm is the wavelet transform method, which is equivalent to pixel + feature fusion. The limitation of current image fusion is that there is no clear and reliable standard for judging the quality of fused images, and it is difficult to fuse different spatial resolutions without sufficient information for fusion. image. One of the untapped development trends of image fusion technology is to use big data and computer deep learning to improve the fusion method and improve the accuracy of image fusion.

4.3. Motion arifacts

Changes in the patient's heartbeat, respiration, blood sugar, etc. will lead to changes in the tumor location and movement patterns. Due to the different imaging speeds of different modalities, the size of the observed lesion area is different. For example, PET/CT imaging, CT imaging time is fast (second level), PET imaging time is very slow (more than 10 minutes), resulting in the average value of tumor movement position observed by PET, increasing the difficulty of image registration and fusion. The attenuation correction effect of PET is also reduced. The motion artifacts caused by breathing, and the differences in images acquired by PET and CT in one breathing cycle are shown in Figure 13.

Commonly used solutions include:

1. Using slow CT, the disadvantage is that it will greatly increase the additional ionizing radiation dose received by the patient [18].

2.The average position imaging method estimates the expiratory cycle and obtains several PET/CT fusion images of different respiratory phases in one respiratory cycle [19] and obtains several PET/CT fusion images of different respiratory phases in one respiratory cycle, so as to obtain a time-weighted average position of the internal structures of all organs including tumors. Compared with 4D imaging, the method is simple, low cost, and has a higher signal-to-noise ratio, and removes the systematic error of direct 3D imaging and the actual position deviation, narrows the safety margin of target area delineation, improves treatment efficiency, and protects surrounding normal tissues.

3. Respiratory gating technology is a commonly used solution, which refers to the combination of images collected by 4DCT and respiratory depth through non-invasive markers [20], and the relative position of markers and tumors to correctly assess the movement of tumors during the respiratory cycle and relative treatment room position changes. However, the relative position of the marker and the tumor itself changes, and the accuracy of this method needs to be improved.

4. Event Tracking Technology tracks and classifies each annihilation event of PET, finds rules, and calculates organ movement trajectory [21].

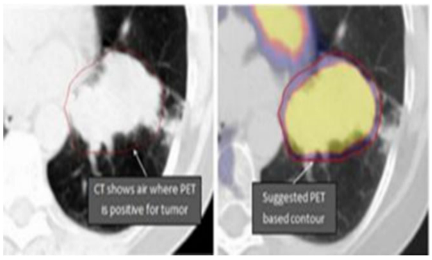

Figure 13. Differences between CT and PET imaging.

4.4. Other challenges

There are several additional challenges that impact the quality of multimodal imaging and the effectiveness of target volume delineation. These challenges include the substantial computational demands associated with multimodal image registration and fusion, which far exceed those required for single imaging techniques [17]. The time-consuming nature of multimodal imaging and fusion, coupled with potential concerns about additional radiation exposure to the human body, can affect the practical application of multimodal imaging [18].

To address these challenges and improve the efficiency of multimodal imaging, future developments may involve leveraging computer vision and big data analytics to optimize image registration and fusion algorithms. Additionally, methods like GPU acceleration can be employed to reduce computational requirements and enhance processing speed [4].

Furthermore, the widespread adoption of all-in-one machines for multimodal imaging may be hindered by their high cost [3].

In the realm of biomedical imaging, [22] have presented a project that applies bio-inspired swarm intelligence for communication-free group object recognition, with a specific focus on neighbor observation.

Liu [23] using advanced machine learning with MRI data to detect early-stage Alzheimer's Disease and aims to create a predictive model for disease progression. [24]study utilizes the Random Forest Tree method to enhance the classification of lengthy biomedical text documents related to cancer, addressing the challenge of processing research papers exceeding 6 pages in length.

Additionally, in the field of diabetic retinopathy detection, W. [25-28] have introduced Twins-PCPVT, a model designed to improve accuracy by capturing both global and local features in fundus images.

5. Conclusion

Multimodal imaging has emerged as a valuable tool in oncology, offering significant advantages over single imaging modalities in terms of tumor detection, diagnosis, staging, and treatment planning. Despite the numerous challenges faced in implementing multimodal imaging, such as image registration and fusion difficulties, respiratory motion artifacts, and the need for optimized algorithms and hardware advancements, ongoing research and technological advancements hold promise for the future of multimodal imaging in oncology. As we continue to improve image registration and fusion algorithms, streamline computational processes, and develop more cost-effective all-in-one machines, multimodal imaging is poised to play an increasingly vital role in the diagnosis and treatment of cancer.

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