# Optimizations of Q. Clear image reconstruction method for brain $^{18}F$ PET/CT studies

By

**LYU XIN**

**Dissertation submitted in partial fulfilment.**

**of the requirement for the degree of**

**Bachelor's Health Science (Honors)**

**(Medical Radiation)**

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# CERTIFICATE

This is to certify that the dissertation is entitled:

"Optimizations of Q. Clear Image Reconstruction Method for Brain 18F-FDG PET/CT Studies"

submitted by

LYU XIN (Matric No.: 155783)

in partial fulfillment of the requirements for the degree of Bachelor of Health Science (Medical Radiation) under the supervision of Dr. Mohd Syahir Mansor, is a bona fide record of original work conducted by the candidate during the academic session 2024/2025.

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Signature of Supervisor: _____

Name: Dr. Mohd Syahir Mansor

Date: JULY 2025

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# ABSTRAK

Latar Belakang: Pengimejan PET/CT otak menggunakan $^{18}$F-FDG memainkan peranan penting dalam menilai metabolisme otak dan mengesan penyakit neurologi. Walau bagaimanapun, dalam pengimejan dinamik dengan bingkai jangka pendek, kualiti imej sering terjejas oleh hingar tinggi akibat statistik kiraan yang rendah. Algoritma pembinaan semula Q. Clear (BSREM) menawarkan potensi penambahbaikan melalui pengubahsuaian parameter penalti β, tetapi nilai optimum β bagi setiap tempoh bingkai masih belum jelas.

Kaedah: Satu kajian dijalankan menggunakan fantom otak Hoffman 3D yang diisi dengan 185 MBq $^{18}$F-FDG. Data diperoleh dalam mod senarai dan dibahagikan kepada lima tempoh bingkai: 10 s, 30 s, 2 min, 5 min dan 30 min. Gambar dibina semula menggunakan algoritma Q. Clear dengan 20 nilai β berbeza (50–1000). Petunjuk kualiti imej dinilai berdasarkan RC% (pekali pemulihan) dan SNR (nisbah isyarat kepada hingar). Pengoptimuman Bayesian digunakan untuk mengenal pasti β terbaik bagi setiap tempoh bingkai di bawah tiga strategi pemberat: keutamaan RC%, keutamaan SNR dan seimbang.

Keputusan dan Kesimpulan: Nilai β yang tinggi (≥950) didapati sesuai untuk bingkai 10 s dan 30 s bagi menindas hingar yang kuat. Walau bagaimanapun, nilai pertengahan (sekitar β = 650) menunjukkan prestasi terbaik dari segi keseimbangan antara kejelasan anatomi dan kestabilan kuantitatif dalam bingkai 2 hingga 30 minit. Berdasarkan penilaian visual dan metrik kuantitatif, β = 650 disyorkan sebagai nilai sejagat untuk pembinaan semula Q. Clear dalam pengimejan PET otak yang dinamik, dengan potensi penggunaan dalam protokol adaptif masa hadapan.

# ABSTRACT

**Background:** Brain $^{18}$F-FDG PET/CT is a crucial tool in assessing cerebral metabolism and diagnosing neurological conditions. However, dynamic acquisitions with short frame durations suffer from low count statistics and high noise levels, posing challenges for both image quality and quantification. The Q. Clear (BSREM) reconstruction algorithm introduces a β penalization parameter to improve image clarity, yet the optimal β setting for each frame duration remains unclear.

**Methods:** A phantom study was conducted using a Hoffman 3D brain phantom filled with 185 MBq of $^{18}$F-FDG. List-mode PET data were acquired and divided into five frame durations: 10 s, 30 s, 2 min, 5 min, and 30 min. Images were reconstructed using Q. Clear with 20 β values (ranging from 50 to 1000). Image quality was assessed using recovery coefficient (RC%) and signal-to-noise ratio (SNR). A Bayesian optimization framework was applied to identify the optimal β under three prioritization strategies: RC%-priority, SNR-priority, and balanced.

**Results and Conclusion:** High β values (≥950) were optimal for 10 s and 30 s frames to suppress severe noise, while mid-range values (β ≈ 650) achieved the best trade-off between anatomical clarity and quantitative stability for 2–30 min frames. Based on both visual interpretability and quantitative performance, β = 650 is recommended as a general-purpose reconstruction setting for Q. Clear in dynamic brain PET imaging, with potential for implementation in future adaptive protocols.

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# List of Abbreviations

| | |
|---|---|
| BPL | Bayesian Penalized Likelihood |
| BSREM | Block Sequential Regularized Expectation Maximization |
| BV | Background Variability |
| COV% | Coefficient of Variation (Percentage) |
| CSF | Cerebrospinal Fluid |
| EANM | European Association of Nuclear Medicine |
| FDG | Fluorodeoxyglucose |
| FWHM | Full Width at Half Maximum |
| GE | General Electric (Healthcare) |
| GM | Gray Matter |
| IPPT | Institut Perubatan dan Pergigian Termaju (Advanced Medical and DentalInstitute) |
| JSNM | Japanese Society of Nuclear Medicine |
| MRI | Magnetic Resonance imaging |
| NIfTI | Neuroimaging Informatics Technology Initiative |
| OSEM | Ordered Subset Expectation Maximization |
| PET | Positron Emission Tomography |
| PVE | Partial Volume Effect |
| RC% | Recovery Coefficient (Percentage) |
| ROI | Region of Interest |
| SBR | Signal-to-Background Ratio |
| SD | Standard Deviation |
| SNR | Signal-to-Noise Ratio |
| SUV | Standard Uptake Value |
| TOF | Time-of-Flight |
| VOI | Volume of Interest |
| WM | White Matter |

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# Chapter 1：INTRODUCTION

## 1.1 Introduction

Positron emission tomography (PET) has become a valuable tool for studying brain function, especially for diagnosing neurological diseases and studying metabolic abnormalities. Among the many radiotracers, 18F-fluorodeoxyglucose (18F-FDG) remains the most used because it can mimic glucose metabolism and accumulate in metabolically active brain tissues such as the cerebral cortex. This property allows clinicians and researchers to visualize and quantify brain glucose utilization, which is critical for evaluating neurodegenerative diseases, epilepsy, and other diseases.

However, acquiring high-quality and quantitatively accurate PET images in brain research is particularly difficult due to the complex anatomy and significant metabolic heterogeneity of brain tissue. These challenges are further exacerbated in dynamic PET imaging because the acquisition process is divided into multiple short time frames to capture tracer dynamics. Short frames, especially in the early stage after injection (e.g., 10-30 seconds), are characterized by low counting statistics and high noise levels, which reduce image interpretability and quantitative fidelity. Therefore, robust image reconstruction methods are essential to preserve spatial details and maintain quantitative accuracy.

The Q. Clear algorithm (also known as BSREM - Block Sequential Regularized

Expectation Maximization) developed by GE Healthcare provides an advanced reconstruction framework that combines noise suppression with fully iterative convergence by applying a penalty factor β. By adjusting β, the user can tune the trade-off between image smoothness and detail preservation, enabling flexible optimization under a wide range of imaging conditions. However, the optimal β value remains case-dependent, especially in dynamic imaging, where statistics and temporal resolution vary widely between frames.

## 1.2 Problem Statement

In dynamic brain PET imaging, acquisition must start immediately after tracer injection to accurately capture early tracer kinetics. This requires segmenting the scan into multiple short frames, typically lasting only 30 to 60 seconds. These short frames result in extremely limited photon statistics, which induce elevated noise levels, blurred anatomical boundaries, and unreliable quantification. Traditional reconstruction methods such as OSEM fail under these conditions due to their incomplete convergence and poor noise control. While Q. Clear reconstruction offers a promising alternative by employing penalized likelihood regularization, the optimal β parameter setting for different frame durations remains unclear. While GE Healthcare generally recommends a β value between 350 and 600 for adult brain PET imaging, emerging research suggests that the optimal setting can vary significantly depending on frame duration, noise levels, and clinical scenarios such as pediatric or obese patient imaging.

Lower β values (e.g., 50–150) can enhance contrast recovery but amplify noise, which may be beneficial for short-frame dynamic acquisitions or low-dose protocols. Higher β values (e.g., 800 – 1000) provide excellent noise suppression but carry the risk of over smoothing, potentially reducing the detectability of lesions in fine anatomical structures. Existing literature lacks a comprehensive evaluation of how β affects quantification accuracy (e.g., RC%) and noise performance (e.g., SNR) under ultra-short dynamic frames.

## 1.3 Aim of Study

**General Objective:**

To optimize image reconstruction methods for brain PET imaging under low-count, short-frame conditions to improve diagnostic and quantitative accuracy.

**Specific Objectives:**

1. To evaluate the effect of varying β-penalized parameters on noise suppression and spatial resolution in dynamic brain PET imaging.
2. To compare the quantitative performance of Q. Clear (in terms of RC% and SNR) across different β values and frame durations.
3. To implement a Bayesian optimization strategy to identify the optimal β value for each frame duration based on multi-objective criteria.

## 1.4 Significance of Study

This study has important implications for both clinical practice and academic research. Clinically, optimizing PET reconstruction in dynamic imaging can enhance the detectability of early-phase metabolic changes, which is crucial for accurate lesion localization in epilepsy, Alzheimer's disease, and other neuropsychiatric conditions. It also supports more reliable extraction of arterial input functions and time-activity curves for kinetic modeling. From a research standpoint, this study systematically investigates the influence of β regularization across a wide range of imaging conditions, providing new insights into the trade-offs between quantification accuracy and noise suppression. The proposed Bayesian

optimization framework can serve as a template for parameter selection in other PET reconstruction scenarios, including multi-center harmonization efforts. This work contributes to improving image quality, quantitative consistency, and clinical confidence in brain PET imaging.

# Chapter 2：LITERATURE REVIEW

## 2.1 Introduction to PET Imaging

Positron emission tomography (PET) is a non-invasive functional imaging technique that uses the paired 511keV γ photon signals generated by the annihilation of positrons and electrons emitted by the tracer to perform three-dimensional reconstruction and quantitatively reflect the physiological processes in the body. The commonly used tracer in brain research is $^{18}$F-fluorodeoxyglucose ($^{18}$F-FDG), which enters neurons through glucose transporters as a glucose analog. After phosphorylation, it undergoes metabolic trapping in the cell, thereby enriching in metabolically active tissues. PET scanners calculate the distribution of tracers in brain tissue by simultaneously detecting a pair of γ photons generated by positron annihilation, thereby achieving quantitative imaging. Since PET itself lacks anatomical resolution and is affected by photon attenuation, low-dose CT is often combined with PET in clinical practice today. The attenuation correction of PET signals is performed through CT images and precise anatomical registration is provided, thereby significantly improving the quantitative accuracy and positioning accuracy of PET images.

In the fields of neurodegenerative diseases and epilepsy, brain PET imaging has important clinical value. $^{18}$F-FDG PET is regarded as the gold standard for assessing brain glucose metabolism. In dementias such as Alzheimer's disease, it is seen that the metabolism of specific brain regions (such as the temporal parietal cortex) is reduced,

while in the intermittent period of patients with refractory epilepsy, FDG-PET can reveal the low metabolic area corresponding to the attack focus. In dynamic PET scans of the brain, the early frame is usually only a few seconds, and the photon counts collected are very low, resulting image noise and a large quantitative fidelity.

Low counts and high noise and high noise problems make the image reconstruction of dynamic PET extremely challenging, and an optimized reconstruction strategy is required to balance noise suppression and resolution. The researchers proposed to use Bayesian regularized iterative reconstruction algorithms (such as GE's) to improve the image quality of dynamic PET: an appropriate penalty factor β can significantly improve image contrast and signal-to-noise ratio, but too strong a penalty will sacrifice the discernibility of small structures. Tian et al. (2023) verified Q. Clear reconstruction on a PET/MR system and found that compared with traditional OSEM, can significantly improve the signal-to-noise ratio and accuracy, but its spatial resolution gradually decreases with the increase of β value. Lysvik et al. (2023) also emphasized that for dynamic PET, a specially designed reconstruction strategy must be used to control the high noise of early frames to maintain quantitative accuracy. In summary, optimizing dynamic PET reconstruction methods in the context of current brain PET research is one of the cutting-edge topics to improve the accuracy and reliability of imaging quantification.

In PET quantitative verification and instrument calibration, the Hoffman

three-dimensional brain phantom plays a key role. The phantom is based on the MRI anatomy of a healthy human brain and is composed of 19 plastic plates with a thickness of about 7 mm. Each plate is engraved with grooves that simulate gray matter, white matter, and cerebrospinal fluid partitions. After filling with ^18F-FDG solution, the GM: WM activity ratio is set to 4:1 (typical healthy brain gray and white matter metabolic ratio), thereby providing a known "true value" as a benchmark for PET system performance evaluation. The anatomically accurate phantom can be used to evaluate partial volume effects and system spatial resolution: for example, by comparing the deviation of the gray and white matter activity concentration recovery coefficients in the reconstructed image from the known 4:1 input ratio, the quantization error of the algorithm can be quantitatively analyzed; and by measuring the size of resolvable structures at the high-contrast gray-white interface, the effective resolution of the imaging system can be evaluated. The Hoffman brain phantom has important application value in brain PET quantitative imaging verification, partial volume effect evaluation, spatial resolution verification, system calibration, etc. With its advantages of high repeatability, strong anatomical authenticity, and multi-center comparability, and provides a standardized benchmark for the optimization of reconstruction algorithms.

## 2.2 Reconstruction Algorithm

The algorithm is an iterative reconstruction method based on Bayesian penalized likelihood (BPL) launched by GE. Its implementation adopts the Block Sequential Regularized Expectation-Maximization (BSREM) algorithm. The algorithm adds a relative difference penalty term to the traditional OSEM iterative formula and combines point spread function (PSF) modeling to suppress the noise generated as the number of iterations increases. With the introduction of the penalty term, it can continue to iterate to a convergent state, thereby achieving "full convergence" reconstruction. In the algorithm, the regularization factor β determines the strength of the penalty term: the larger the β value, the stronger the image smoothness and the smaller the noise, but the spatial resolution may decrease; the smaller the β value, the sharper the reconstructed image, but the noise increases. In summary, balances resolution and noise through the β parameter, achieving the unity of convergence iteration and noise suppression.

Compared with the traditional OSEM algorithm, it has significant differences. Due to the rapid accumulation of noise, the OSEM algorithm usually needs to terminate the reconstruction when the number of iterations is very small, resulting in insufficient convergence of the results, thereby introducing quantitative errors such as positive bias in low-count regions, negative bias in high-count regions in high-count areas. The penalty term in can effectively control noise and will not generate excessive noise even when the number of iterations increases, so it can achieve more complete convergence. Tian et al. (2022) pointed out that compared with OSEM, can achieve full image convergence and provide more accurate quantitative results and higher signal-to-noise

ratio. Lantos et al. (2018) also found in phantoms and clinical trials that BSREM is superior to OSEM in contrast recovery and image uniformity and is particularly suitable for scanning under low-count conditions. However, a higher β value (⩾350) is required to avoid noise and artifacts. These studies show that it can suppress noise while ensuring iterative convergence by adding regularization penalties to the objective function, thereby surpassing the performance bottleneck of traditional OSEM.

In comparative studies on image quality, it also showed advantages. In general, reconstruction can obtain higher signal-to-noise ratio (SNR) and better image details. Ribeiro et al. (2021) found in a PET/MR brain study that not only improved contrast recovery but also outperformed OSEM in resolution and SNR; especially when a larger β value was used, could significantly improve the SNR of the image. Tian et al. (2022) also reported in PET/MR clinical data that compared with OSEM+TOF (Time-of-Flight) reconstruction, (β=400) increased the median lesion signal-to-noise ratio by 138%, the signal-to-background ratio (SBR) by 59%, and the noise level by 38%. In the field of dynamic imaging, the latest research further highlights the advantages of. Springer et al. (2025) pointed out in a study of dynamic whole-body PET/CT that Q. Clear reconstruction can reduce the noise level of all tissue types by 40%–55% compared with OSEM. For small volume regions of interest (VOI), showed higher accuracy in estimating the $^{18}$F-FDG uptake rate. In summary, it shows better signal-to-noise ratio, higher contrast recovery and better quantitative accuracy than OSEM in both static and dynamic reconstruction.

The advantages of are particularly obvious in brain PET and dynamic PET imaging.

Brain PET studies often require high spatial resolution and linear response for dynamic quantitative modeling, but on current PET/MR systems, filtered back projection (FBP) reconstruction is often not supported, and only iterative methods such as OSEM can be used. However, OSEM will lead to low-count area bias due to early stopping, affecting the results of dynamic analysis. Ribeiro et al. (2021) pointed out that reconstruction with low β values can approximate FBP-like linearity equivalent to FBP, making it suitable for brain PET dynamic studies while still maintaining a higher signal-to-noise ratio than OSEM. This advantage is more important under low-count short-frame conditions. Emblem et al. (2023) found in their study on dynamic brain PET that for small structures (<10mm) and short-frame data, using lower β values will lead to increased variability and overestimation of activity, while increasing β values can reduce variability but with slight underestimation. They suggested that for dynamic quantification of small structures, β≈300–500 can be used to balance precision and accuracy between accuracy and precision. In addition, the dynamic whole-body study by Springer et al. (2025) also showed that can significantly reduce the noise of the time series curve in short-term high-noise data and improve the accuracy of metabolic rate estimation for small VOIs. In summary, can effectively suppress noise and improve the signal-to-noise ratio in brain PET (especially dynamic low-count short frames), and maintain high resolution and quantitative linearity by appropriately selecting the β value, providing a more reliable image basis for quantitative analysis of the brain.

## 2.3 Impact of Reconstruction Parameters

Research has shown that in Q. Clear (BPL) reconstruction, there is a typical noise-resolution trade-off between the β value and image quality: a lower β value (β < 200) provides higher contrast and richer spatial detail but also results in noticeable image noise. Conversely, a higher β value (β > 800) significantly suppresses noise and smooths the image, but at the same time significantly reduces image detail and contrast. Therefore, low β values are often used in scenarios where structural detail needs to be emphasized (such as high-resolution imaging), while high β values are suitable for quantitative analysis tasks that are more sensitive to image noise. Related literature indicates that the optimal value of β is not fixed but should be flexibly adjusted according to the specific imaging task. For example, Tian et al. (2022) reported in their 18F-FDG PET/MR study that optimal image quality is achieved when β is approximately 400; Lysvik et al. (2023) recommended using β ≈ 300–500 for imaging small structures, while higher β values are acceptable for larger structures; and Ribeiro et al. (2021) reported that the optimal β value for brain imaging is between 100 and 200 in a specific PET/MR system. These results suggest that the choice of β needs to be dynamically adjusted based on structure size, acquisition time, and imaging objectives. Furthermore, the interaction between frame length and β can significantly affect image quality: in the low-count state of short frames (e.g., 10 seconds), the number of photons is extremely low, and Poisson noise becomes the dominant factor. In this case, a higher β value is required to suppress image noise. However, in long frames, due to the reduced quantum noise, using a high β value (e.g., 400–500) may oversmoothed the true signal.

Therefore, shorter frame lengths generally require higher β values to stabilize reconstruction, while longer frame lengths can reduce β values to preserve image detail. Lysvik et al. (2019), through simulations of different frame lengths and spherical targets, found that using lower β values for short frame lengths resulted in higher image variability, while using higher β values effectively reduced noise variability and improved reconstruction stability. However, with sufficiently long frame lengths (e.g., 30 minutes), the image itself has sufficient counts and low noise, and the marginal impact of β on image quality is reduced. However, excessively high β values can still cause image detail blurring and over smoothing. For example, Ribeiro et al. found that in brain PET experiments, using β = 100 achieved optimal spatial resolution, while β = 1000 significantly improved the signal-to-noise ratio (SNR) but also sacrificed significant image detail. Similarly, Yoshii et al. (2020) observed that as β values increased, image contrast decreased while noise gradually decreased. This suggests that even under high-count conditions, the upper limit of β must be carefully controlled to avoid compromising the diagnostic value of the images. Overall, the choice of β should comprehensively consider the scale of the imaged structure, frame length, noise tolerance, and research objectives: short-frame reconstruction requires a higher β to ensure stability and usability, while long-frame reconstruction can be appropriately reduced to better preserve image structure and detail.

Furthermore, studies have shown that increasing the β value from 800 to 1000 leads to a consistent improvement in image SNR, a more uniform background, and no significant loss of image detail. Lindström et al. (2019) reported that in whole-body PET studies,

using a β = 900 reconstruction yielded an approximately 60% improvement in image SNR compared to conventional OSEM, clinically assessed as the upper limit of good image quality and diagnostic margins. Within the β = 900–1000 range, images exhibited stable signal-to-noise ratios and acceptable image clarity, with only a slight decrease in edge sharpness compared to β = 800. While metrics such as full width at half maximum (FWHM) remained within clinically acceptable limits, when β ≥ 1300, while noise continued to decrease and the background of small lesions became more organized, image contrast and structural margins significantly degraded, making them considered unsuitable for clinical diagnosis. Tian et al. (2022) similarly advised against using reconstruction values exceeding β = 1000, noting that when β > 1000, the contrast recovery coefficient (CR) significantly decreased, compromising quantitative accuracy and image resolution. As shown in Figures 2.3 (a) and 2.3 (b) (from the results published by Lindström et al. and Tian et al., respectively), while excessively high β values can improve SNR, they can also lead to excessive image smoothing, reduced contrast, and decreased spatial resolution, ultimately compromising diagnostic image quality. Therefore, during PET image reconstruction, the β value should strike a balance between optimizing noise suppression and preserving detail. Specifically, the parameter selection should be tailored to the frame length and the specific imaging task.

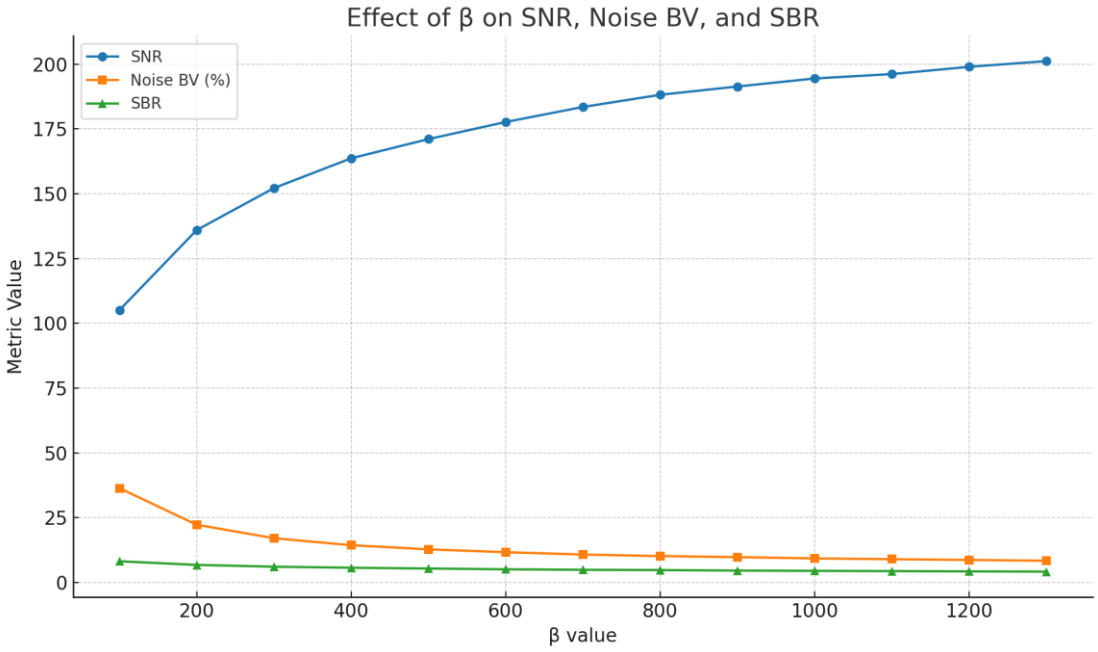


*Figure 2.3 (a): Effect of β on SNR, noise background variability (BV), and signal-to-background ratio (SBR) based on phantom data reconstructed using BSREM algorithm. Data adapted from Lindström et al. (2019).*

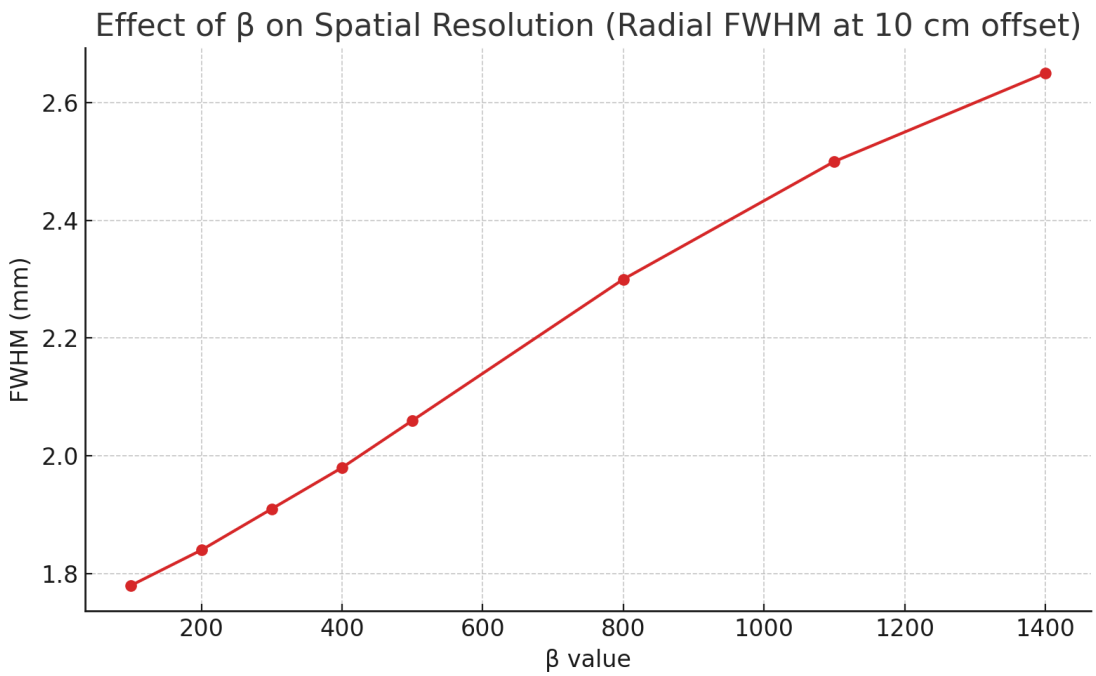


*Figure 2.3 (b): Radial full width at half maximum (FWHM) at 10 cm offset under different β values, showing spatial resolution degradation trend. Data adapted from Tian et al. (2022).*

## 2.4 SUV and image quality

### 2.4.1The SUV and algorithm

The standardized uptake value (SUV) is a commonly used semi-quantitative indicator, but its accuracy is affected by multiple factors such as the imaging system and reconstruction algorithm. Limited spatial resolution will produce partial volume effect (PVE), and SUV, as a key semi-quantitative indicator of neurodegenerative diseases, is constrained by PVE and noise, which may lead to a low recovery coefficient for SUV measurement of small lesions.

Under different reconstruction algorithms, the volatility of SUV is also different. In order to maintain the consistency of SUV quantification, it is necessary to rely on advanced reconstruction algorithms and parameter calibration strategies. The Bayesian penalized likelihood reconstruction (Q. Clear) developed by GE healthcare improves the consistency of SUV measurement while suppressing noise by introducing a regularization term. Lindström et al. 2019 found that under the same noise level, BSREM can significantly increase tumor SUV_max (by about 11%). More importantly, by optimizing the penalty coefficient β, BSREM can shorten the scanning time while maintaining image quality comparable to traditional OSEM iterations, thereby considering both SUV measurement reliability and image clarity. In general, the above standardization and calibration strategies can alleviate the contradiction between SUV quantitative accuracy and image quality to a certain extent.

## 2.4.2 Evaluation indicators: RC% and SNR

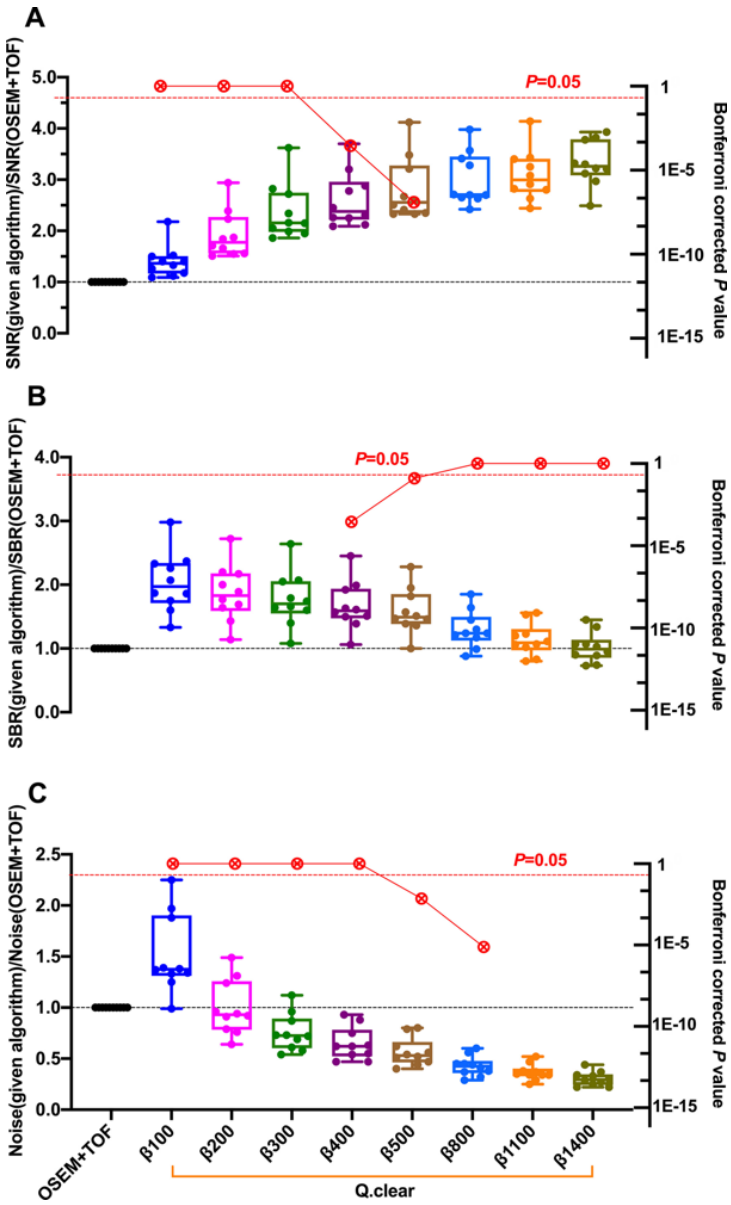


*Figure 2.4.1 Comparison of image quality indicators of Q. Clear (BSREM) and OSEM+TOF reconstruction under different β values. A, B, and C in the figure are normalized box plots of SNR, signal-to-noise ratio (SBR), and noise level, respectively. When β≈400, Q. Clear achieves the peak SNR and a signal-to-noise ratio significantly higher than OSEM. The image adapted from: Tian et al.2022, "The effect of Q. Clear reconstruction on quantification and spatial resolution of 18F-FDG PET in simultaneous PET/MR," EJNMMI Physics.*

**The recovery coefficient (RC%)** is an indicator to measure the quantitative recovery ability of the reconstructed image, which is usually defined as the ratio of the measured concentration in the region of interest to the true concentration. The higher the RC%, the more sufficient the image is for quantitative recovery of small lesions.

**The signal-to-noise ratio (SNR)** reflects the statistical stability of the image, which is defined as the ratio of the target signal intensity to the background noise. Together, they constitute the key indicators for image quality assessment.

In image reconstruction, it is often difficult to achieve both high RC% and high SNR at the same time. The experimental results shown in Figure 1 show that with the increase of the penalty parameter β, the image contrast (CR) and noise level decrease significantly, while the SNR increases; when β≈400, the SNR of Q. Clear reaches a peak value and is significantly higher than that of traditional OSEM+TOF reconstruction. In other words, increasing β can improve SNR (smoother images and lower noise), but will reduce RC% (loss of image details and compression of contrast). This typical relationship between RC–SNR requires us to make a trade-off when selecting reconstruction parameters.

To achieve a balance between RC% and SNR, a multi-objective optimization method can be used. For example, a Bayesian optimization framework can be constructed to set a weighted objective function for a given application task, jointly examine RC% and SNR, and automatically search for an excellent β value range to simultaneously meet the requirements of quantitative accuracy and image quality. Through this strategy,

reconstruction parameters can be flexibly adjusted according to actual diagnostic or quantitative analysis goals to achieve optimal image reconstruction performance.

### 2.4.3 Quantification challenges under dynamic PET

Dynamic PET imaging divides the acquisition time into multiple short time frames to capture the pharmacokinetic process, but the counts in the short frames are significantly reduced, resulting in a significant increase in noise. Currently, the partial volume effect still exists, the recognition rate of small structural lesions is low, and the statistical noise makes it difficult to estimate RC% stably. On the other hand, excessive pursuit of high RC will reduce the contrast between lesions and background and increase the risk of missed diagnosis of small lesions. "In general, it is difficult to ensure accurate SUV measurement by traditional iterative algorithms alone in extremely high noise environments.

Using a higher penalty factor β in short frames can effectively reduce noise and improve SNR, but at the cost of reducing RC% (smoother images and reduced grayscale contrast). This means that a trade-off between high β and low β is required in dynamic reconstruction: the former helps stabilize the signal and improve the availability of time-resolved frames, while the latter maintains contrast and resolution.

The optimization of dynamic imaging depends on the specific quantitative task and the size of the target structure. For dynamic parameter imaging or small lesion assessment that requires high temporal resolution, it may be necessary to sacrifice some SNR to obtain sufficient details, while for situations where only gross quantitative trends are

required, it is acceptable to use higher β values to improve SNR. In summary, in dynamic PET reconstruction, the balance between high RC% and high SNR needs to be comprehensively selected based on application requirements, target structure characteristics, and system noise level.

# Chapter 3：MATERIALS AND METHODS

## 3.1 Materials

### 3.1.1 Hoffman 3D Brain Phantom

Hoffman et al. (1991) developed a three-dimensional brain phantom to simulate clinically realistic radioactivity distributions in PET imaging. The design, based on a T1-weighted MRI of a healthy human brain, consists of 19 stacked slices (each 7 mm thick) milled from fluorite plates with alternating groove patterns. These grooves form interconnected compartments filled with $^{18}$F-fluorodeoxyglucose (FDG) solution to emulate gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) at a relative activity ratio of 4:1:0—reflecting typical $^{18}$F-FDG PET uptake contrasts. This anatomically accurate phantom allows for direct comparison between reconstructed images and a known ground-truth reference, facilitating robust quantitative evaluation of image quality and reconstruction algorithm performance.

In this study, the Hoffman phantom was filled with 185 MBq of $^{18}$F-FDG to provide clinically relevant count statistics and activity distribution for assessing β-penalized reconstructions. Three key aspects were evaluated: (1) RC% error quantification by comparing GM/WM ratios against the known 4:1 ground-truth, thereby revealing regularization-induced bias; (2) analysis of the noise-resolution trade-off, where

high-contrast GM/WM boundaries reveal spatial resolution degradation at high β values, and uniform WM regions assess noise suppression efficiency; and (3) emulation of dynamic PET conditions by segmenting the 30-minute acquisition into multiple frame durations (10 s, 30 s, 2 min, 5 min, 30 min), enabling investigation of β's influence across varying statistical conditions.

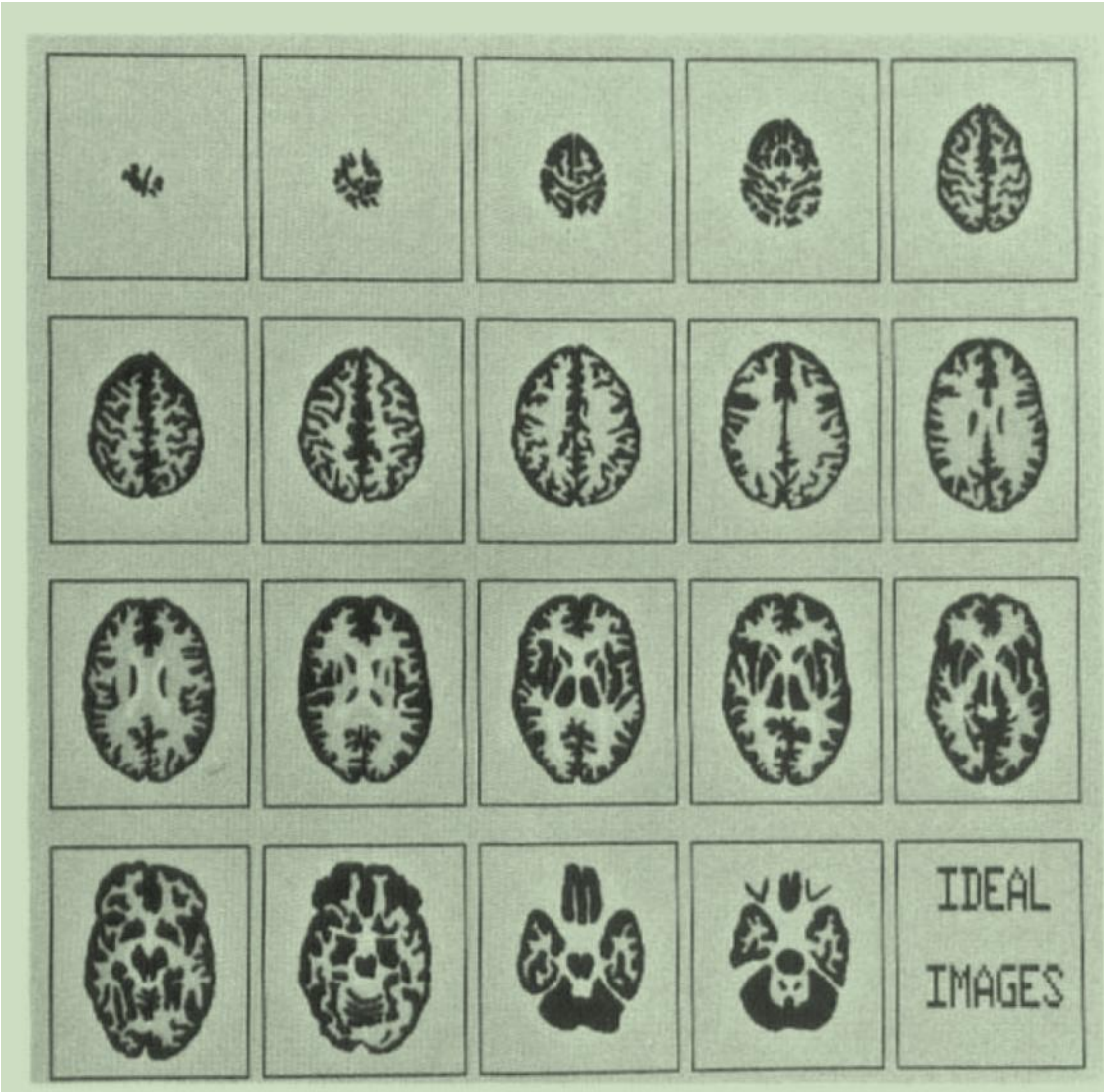


*Figure3.1.1: Trilevel fluorodeoxyglucose images illustrating the gray matter, white matter, and cerebrospinal fluid compartments used in the fabrication of the Hoffman 3D brain phantom. These images are adapted from Hoffman et al. (1991), where anatomical outlines*