SyneRBI Exchange Programme Report

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1 Motivation for the Project and Hopes for Outcome

The primary aim of this project was to successfully read and utilise listmode data from the Siemens Biograph Vision and Siemens Biograph Vision Quadra scanners. Using phantom or patient data from the University Medical Centre Groningen, the goal was to generate data necessary for developing motion detection and motion tracking algorithms. One potential candidate for motion detection explored was Bottom-Up Segmentation (BUS), which could be used with listmode data to achieve high temporal and spatial resolution in motion detection.

2 Summary of Proposal and Achievements

In the initial project proposal (Sec 6), we outlined the following key goals:

1. Enable listmode reconstruction for Siemens Biograph Vision and Quadra.
2. Reconstruct patient data using STIR.
3. Implement motion detection using change point detection techniques.

We also defined the expected outcomes:

1. Successful reconstruction of Siemens Biograph Vision and Quadra listmode data.
2. Implementation of motion detection, data framing, and motion-compensated image reconstruction using listmode on a high-performance computer.

3 Summary of Project Output

The output of this project has been twofold:

- Successfully reading Siemens Vision non-Time-of-Flight (non-TOF) listmode data.
- Evaluating the effectiveness of Bottom-Up Segmentation, a statistical method from the change point detection family, for identifying time points at which motion occurred.

3.1 Reading Siemens Vision non-TOF Listmode Data

We successfully decoded the Siemens Vision non-TOF listmode data (see Section **??** for technical details) using GATE simulation. By emitting photons into two known block pairs, we were able to map Siemens listmode variables into STIR's detector coordinate system. The output from STIR reconstruction of a Hoffman

phantom closely matched the reconstruction from e7tools, with minor differences such as:

1. Axis flips.
2. Increased noise due to the absence of TOF data.

This process now enables patient data reconstruction, although time constraints prevented further investigation in this area.

3.2 Motion Detection using Bottom-Up Segmentation

We aimed to use Vision listmode data for automatic motion detection and framing. However, due to the complexity of decoding the Vision listmode and the time spent on that task, we were unable to fully implement motion detection on this scanner. Nevertheless, we achieved promising preliminary results by applying the Bottom-Up Segmentation algorithm to a dataset from a different PET scanner.

Simulation results demonstrated that the Bottom-Up Segmentation algorithm is highly sensitive to motion, detecting displacements as small as 2mm during 10 seconds of no motion, and displacements as small as 3mm during shorter intervals of 4-6 seconds. For more details, refer to "Rigid Motion Detection for Abrupt Motion in FDG Brain PET Imaging" in Appendix 3.

4 Limitations and Further Steps

Unfortunately, we were unable to access Siemens Quadra listmode data, as it is confidential and not publicly available. However, the code and experiments developed in this project can be applied to Quadra data in the future.

In conclusion, while we were unable to perform motion detection, tracking, and correction on Vision and Quadra listmode data as initially hoped, we did successfully implement these processes on a different PET scanner. Given the ability to read Vision and Quadra listmode data, the pipeline we developed should be applicable. Limited time prevented us from fully integrating the two parts of the project.

5 Final Reflections and Future Directions

Overall, the project was a success. Although we did not achieve all the original goals—such as reading Siemens Quadra listmode data or developing a novel motion tracking method—we did achieve significant milestones, including decoding Siemens Vision non-TOF listmode and evaluating a potential motion detection algorithm. The next logical step would be to apply the motion detection algorithm to Vision listmode data from phantom and patient studies for experimental validation.

6 Appendix

CCP-PETMR Funded Researcher Exchange Application

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Institution: University of Leeds, West Yorkshire, United Kingdom.

Host Institution: University Medical Centre Groningen (UMCG), Groningen, Netherlands.

Introduction and Purpose: University Medical Centre Groningen (UMCG) has the Siemens Biograph Vision and Siemens Biograph Vision Quadra installed and we wish to bring this to Software for Tomographic Image Reconstruction (STIR). Further, STIR has motion compensated image reconstruction (MCIR) but unfortunately no motion detection and motion tracking. This is a feature we wish to bring to STIR to complete the motion detection, tracking and correction hence allowing users to perform data driven motion correction right out of the box.

Project Goals / Activities: The project goals are in this order:

1. Enable listmode reconstruction for Siemens Biograph Vision and Quadra in STIR.
2. Reconstruct patient data that has motion in STIR.
3. Implement motion detection using change point detection.
4. Perform motion tracking using a novel method.

Available Data:

1. Phantom listmode data from Siemens Biograph Vision and Vision Quadra (to be made available).
2. Patient data with motion (cannot be made available due to privacy regulations).

Main Output:

1. Reconstruction of Siemens Biograph Vision and Siemens Biograph Quadra data.
2. Perform motion detection, data framing, and motion compensated image reconstruction using listmode on a high performance computer.

Benefits to CCP: The study will add two additional scanners to the STIR's repository with analysis of STIR compared to the commercial software Siemens e7 toolkit. Further any code produced (motion detection and tracking) from this project is intended for contribution to the open-source STIR.

Cost: We kindly request for £9,000 for the duration of the stay in the Netherlands. This will cover the rent and utilities for 9 months from October 2023 to June 2024, which cost £992 a month (1150 Euros). The cost of food, travel, and other expenses will be covered by Viet.

Support from Host Institution: I, Charalampos Tsoumpas, am happy to accept Vet's application to work in University Medical Centre Groningen in the Netherlands to implement Siemens Biograph Vision and

Rigid Motion Detection for Abrupt Motion in FDG Brain PET Imaging

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***Index Terms*—PET, motion detection, change point detection, bottom-up segmentation**

I. Introduction

DATA-driven methods (DDMs) for motion tracking have been gaining attention. One standard DDM for motion tracking is to perform reconstruction every 3-5 seconds of scanning time and produces a stack of 3D image. The images are registered to the reference frame and this generates transformation matrices for motion correction. This is often called frame based motion tracking methods [1] [2] [3]. Another method to avoid reconstruction is to calculate motion from sinogram [4]. While effective in reducing motion artifacts, frame-based methods do not address intra-frame motion meaning motion artefact is still present. It is better to use listmode for motion detection and time segmentation. In this work, we perform motion detection and frame estimation for rigid abrupt motion.

II. Materials and Methods

A. Scanner

Positrigo's NeuroLF is a dedicated brain positron emission tomography (PET) scanner (no CT or MR) with: 8 sides, 48 rings, and 256 detectors per ring. Each detector has 3.2 $\times$ 3.2 $\times$ 10 mm^3. This produces an image of 161 $\times$ 161 $\times$ 95 voxels with a size of 1.6565 mm^3 with a spatial resolution of 2-3 mm at centre of field-of-view (FOV) and 4-5 at edge of FOV.

B. Data Collection

In this investigation, we utilised patient data previously acquired from the Siemens Biograph Vision Quadra. The patient was administered with FDG and underwent scanning for a duration of one hour. From reconstructed dynamic image, we extracted a single frame with minimal motion, which serves as our input data for voxelised Monte Carlo simulation. The patient data has been anonymised, retaining only the images for analysis. The patient images are presented in Figure 1.

This single frame is then fed into GATE using the NeuroLF geometry and the motion is perform using Python using rigid motion (translation and rotation) for each 0.1 seconds. This allows a discrete approximation to continuous motion. Finally, the ROOT is converted into listmode.

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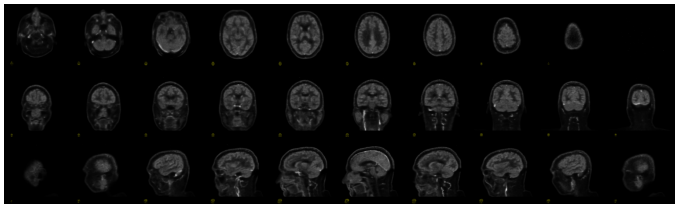

Fig. 1. Images of the patient from axial (top, left to right indicating inferior to superior), coronal (middle, left to right indicating anterior to posterior), and sagittal (bottom, left to right indicating right to left) perspectives. The frames are taken at intervals of every 10 slices, with each slice being 1.65mm isotropic.

C. Convert Listmode to Pseudo-Displacement Time Series

Each coincidence in the data represents a Line of Response (LOR), comprising a pair of detector indices, namely $\{det_A, ring_A, layer_A\}$ and $\{det_B, ring_B, layer_B\}$, along with a timestamp in integer format. The physical location of each detector is denoted by coordinates $\{x_A, y_A, z_A\}$ and $\{x_B, y_B, z_B\}$. Utilising the midpoint of each LOR, we can derive a 3D space coordinate.

D. Change Point Detection & Bottom-Up Segmentation

Consider the following problem represented as $\{(t_i, y_{t_i}) \; | i = 1, ..., n\}$, where $\mathcal{T} = \{t_i | i \in U \subseteq \{1, ..., k\}\}\}$. The set U is called the "index splitting" set while $\mathcal{T}$ serves as the "time splitting" set, dividing the data into $k + 1$ segments, assuming the existence of k points that induce changes in our time series. The objective, using the time series, is to estimate the set $\mathcal{T}$. This estimation can be framed as a minimization problem, expressed as follows:

$$L(\mathcal{T}|\underline{y}, \underline{t}) = \sum_{i=1}^{|\mathcal{T}|} \mathcal{C}\Big(y_j, f(t_j)|t_j \in [t_{i-1}, t_i)\Big) + \lambda \cdot \mathcal{R}(\mathcal{T}) \quad (1)$$

Here, $\mathcal{C}$ denotes the cost function quantifying the fit between the data $y(t)$ and the modeled counterpart $\hat{y}_j = f(t_j)$ within the interval $[t_{i-1}, t_i)$, while $\mathcal{R}(\mathcal{T})$ represents the penalty on the "time splitting" set, and λ determines the strength of this penalty. Unfortunately, due to the discreteness of set $\mathcal{T}$, direct differentiation of L to find the minimum point is not possible, even with a convex function $\mathcal{C}$. Therefore, an iterative method is necessary.

The Bottom-Up Segmentation [7] method is an iterative approach designed for cases where the number of change points (k) is unknown. It can be employed in both online and offline settings, allowing for live segmentation or post-recording analysis. To implement the bottom-up segmentation,

we commence with the maximum number of segments, represented as:

$$\mathcal{T} = \{t_i | i \in U\}, U = \{1, ..., n\}, \text{ Time Splitting Set}$$

This implies the presence of n change points and $n+1$ segments, with the associated cost function defined as:

$$\mathcal{C}(y(t), f(y(t))) = ||\underline{y} - f(\underline{y})||^2, \text{ Cost function}$$

$$f(\underline{y}) = \frac{1}{n} \sum_{j=i-1}^{i} y_{t_j}, \text{ Segment mean}$$

$$\lambda \cdot \mathcal{R}(\mathcal{T}) = \sigma \cdot |\mathcal{T}| \quad , \text{ Penalisation.}$$

In this context, $|\mathcal{T}|$ represents the cardinality (size) of the 'time splitting' set $\mathcal{T}$. The goal of this loss function is to optimise the mean fit within each segment while simultaneously minimising the total number of segments. For instance, maximising the size of $\mathcal{T}$ reduces $\mathcal{C}$ but increases $\mathcal{R}(\mathcal{T})$, which is generally not optimal. Conversely, minimising $\mathcal{T}$ (to an empty set, implying a single segment) minimises $\mathcal{R}(\mathcal{T})$ to zero but both extremes are not ideal. The Bottom-Up Segmentation (BUS) method iteratively evaluates each index $t_i \in \mathcal{T}$, assessing the effect of removing its associated change point. For this study, we will utilize an open-source Python software called Rupture [8] for segmentation of time.

E. Controlled experiment

To test the algorithm we use a few controlled experiment. The first experiment is fixed the time point which motion occurs (every 10 seconds) but the amount of displacement varies (3mm, 2mm, 1mm, 0.5mm) and observed the minimum consistent detection of displacement. The second we perform a fixed incremental displacement (of +3mm) for a varied interval (10s, 8s, 6s, 4s, 2s) between abrupt displacement and observed the minimum consistent detection of motion time points.

III. Results

TABLE I
SPATIAL SENSITIVITY

time(s)	3mm	2mm	1mm	0.5mm
10	10.0	10.0	-	-
20	20.0	18.8	21.3	-
30	30.0	30.1	-	-
40	40.0	41.4	41.4	40.0
50	50.0	50.2	-	-
60	59.8	60.0	60.0	59.9
False neg(%)	0	0	50	66.7
RMSE(s)	0.24	1.87	NA	NA

Estimate time point for motion of 0.5mm, 1mm, 2mm, 3mm of displacement at fixed time interval (10s). "-" represent missing data i.e. false negative while "NA" is not application because calculation can't be performed due to missing data.

From Table I, we observed the that we can detect motion of 2mm displacement for abrupt motion at every 10 seconds consistently. Beyond 2mm there are false negative which may cause motion artefact but with the caveat that below 2mm is beyond the spatial resolution. The root mean squared error for the time point of motion increased as displacement decreases.

TABLE II
TEMPORAL SENSITIVITY

displacement(mm)	10s	8s	6s	4s	2s
3	10.0	8.9	5.0	3.7	3.1
6	18.7	17.2	11.9	8.1	4.4
9	29.9	23.9	16.9	11.8	-
12	40.5	32.1	23.7	16.2	8.1
15	49.2, 49.8	41.0	29.3	-	-
18	59.9	47.9	35.5,36.0	23.9	12.0
False neg(%)	0	0	0	16.7	33.3
False pos(%)	16.7	0	16.7	0	0
RMSE(s)	1.6	1.8	1.8	NA	NA

Estimate time point for motion at fixed 3mm of displacement between varied duration (e.g. for second column, from 0-10 seconds there is 3mm of displacement, 10-20 there is 6mm of displacement etc... "-" represent missing data i.e. false negative, multiple entries in a cell means false positives while "NA" is not application because calculation can't be performed due to missing data.

From Table II, we observe abrupt motion of fixed 3mm can be detected down to 6 seconds (duration between abrupt motion) consistently. While lower means the increase in false negative. Similarly, the RMSE increased as the duration between motion decrease.

A. Discussion

Overall, the listmode tracking provide excellent spatial sensitivity when it comes to motion detection (up to 2mm which is smaller than spatial resolution of scanner) but the temporal sensitivity is lacking with only consistent detection of abrupt motion with time interval of 6 seconds. In practice, it is possible patients will move more than 3mm over a duration less than 6 seconds and so the question is: is it possible to increase temporal resolution for motion detection? It is likely that there is a trade-off between spatial and temporal sensitivity but the algorithm's spatial sensitivity should be tune to match the spatial resolution of the scanner which fixes the temporal resolution. This potentially might be the temporal limit of listmode method.

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