Optimization of Iterative Cardiac I-123 MIBG SPECT Reconstruction

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Introduction

123I- *meta*-iodobenzylguanidine (MIBG) Cardiac SPECT

- Clinical task of MIBG SPECT
  - Estimate Heart-to-Mediastinum Ratio (HMR)
  - Planar or SPECT images

- Improved SPECT images
  - Collimator-detector response compensation
  - Iterative reconstruction

- Optimized reconstruction parameters
  - "Regression without Truth" (RWT)

Introduction

Regression Without Truth (RWT)

- Comparison of estimation methods when true value is unknown
  - Linear model of estimation process
  - Marginalize the data likelihood over the unknown true values
  - Estimate model parameters – “linear regression” without x-axis
  - Model parameters → Figure of merit → Method ranking

- Earlier applications of RWT:
  - Estimation of cardiac ejection fractions
  - Estimation of volume from images
  - Estimation of binding potentials

Introduction

Objective of this study:

- Optimize iterative reconstruction parameters of MIBG SPECT in terms of HMR estimation.

Hypothesis:

- RWT can objectively identify a set of reconstruction parameters that optimizes estimation performance.
Regression Without Truth (RWT)

- Linear model of estimation process:

\[
\hat{\theta}_{pm} = a_m \theta_p + b_m + \varepsilon_{pm}, \quad p = 1, \ldots, P
\]

\[
\varepsilon_m \sim \mathcal{N}(0, \sigma_m^2) \quad m = 1, \ldots, M
\]

- For a given \( p \), the conditional probability density of \( \hat{\theta}_{pm} \) is:

\[
pr\left(\hat{\theta}_{pm} \mid \{a_m, b_m, \sigma_m^2\}, \theta_p\right) = \mathcal{N}_M \left(\{a_m \theta_p + b_m\}, \Sigma\right), \quad \Sigma = \text{diag} \left\{ \sigma_m^2 \right\}
\]

- Marginalize over \( \theta_p \):

\[
pr\left(\hat{\theta}_{pm} \mid \{a_m, b_m, \sigma_m^2\}\right) = \int d\theta_p \, pr(\theta_p) \mathcal{N}_M \left(\{a_m \theta_p + b_m\}, \Sigma\right)
\]
Methods

Regression Without Truth (RWT)

\[ \text{FOM}_m = \frac{\sigma_m^2}{a_m^2} \quad \rightarrow \quad \text{FOM}_{(1)} = \min \{ \text{FOM}_m \} \]

- **Key Assumptions:**
  - Form of \( pr(\theta_p) \) is known: in this work, \( pr(\theta_p; \mu, \eta^2) = \ln \mathcal{N}(\mu, \eta^2) \)
  - Parameters \((\mu, \eta^2)\) estimated with \( \{a_m, b_m, \sigma_m^2\} \)

- **Problems encountered in our application:**
  - ML estimates occurred on boundary of feasible region
  - \( \text{FOM}_{(1)} \) depended strongly on starting point of optimization

- **Both problems were addressed by fixing \((\mu, \eta^2)\)**

Methods

RWT simulations

• Objective of simulations:
  - Investigate the dependence of $FOM_{(1)}$ on:
    1. Choice of $pr(\theta_p)$
    2. Choice of fixed parameters of $pr(\theta_p) : (\mu, \eta^2)$

• Simulated Data:
  - Preliminary RWT on clinical HMR estimates $\Rightarrow \{a_m, b_m, \sigma_m^2\}$
  - Sample true $\theta_p : \begin{cases} \ln \mathcal{N}(\mu, \eta^2) : \text{Mean}(\theta_p) = 7.0, \text{Var}(\theta_p) = 11.0 \\ \text{Weibull}(\lambda, k) \end{cases}$
  - Compute $\left\langle \hat{\theta}_{pm} \right\rangle = a_m \theta_p + b_m$, and add Gaussian noise $\varepsilon_m \sim \mathcal{N}(0, \sigma_m^2)$
  - RWT: $pr(\theta_p) = \{\ln \mathcal{N}(\mu, \eta^2) : \text{Mean}(\theta_p) \in [2.5, \ldots, 25], \text{Var}(\theta_p) \in [6.5, 11.0]\}$
Methods

RWT using clinical MIBG SPECT data

- MIBG SPECT projection data ($P=55$)
  - Iterative reconstruction was optimized with respect to:
    - OSEM iteration number
    - 3D-Gaussian postfilter FWHM
  - HMR estimated for each combination of parameters ($M=36$)

- RWT applied to HMR estimates
  - Bootstrap aggregation (bagging) to reduce overfitting
  - Bootstrap confidence intervals of ($FOM_j - FOM_k$)

- RWT Consistency Checks
  - CC1: checks for consistency of linear model assumption
  - CC2: checks for consistency of assumed $pr(\theta_i)$

Results

RWT simulations

Mean and Relative Standard Deviation of Model Parameters

\[ pr(\theta_p) = \ln \mathcal{N}(\mu, \eta^2) \]

\[ pr(\theta_p) = \text{Weibull}(\lambda, k) \]

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<thead>
<tr>
<th>True</th>
<th>Mean((\theta_p))</th>
<th>Var((\theta_p))</th>
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<td>7.0</td>
<td>11.0</td>
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| RWT  | varied | 6.5 |

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Results

RWT simulations

First 4 order statistics of $FOM_m$

$pr(\theta_p) = \ln N(\mu, \eta^2)$

$pr(\theta_p) = \text{Weibull}(\lambda, k)$

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Four points \( \{m : \Pr \left[ FOM_1 = FOM_m \right] > 0.05 \} \)
- Of these, one point excluded based on 95% CI of \((FOM_j - FOM_k)\)
Results

RWT using clinical MIBG SPECT data

OSEM + CDR(geometric)

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<tr>
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<th>FWHM</th>
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OSEM

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Conclusions

• Simulation results suggest RWT is able to consistently identify the correct FOM\(_{(1)}\)
  – FOM\(_{(1)}\) was not sensitive to choice of \(pr(\theta_p; \mu, \eta^2)\)

• Using clinical data, RWT identified sets of optimal parameters for three reconstruction methods.
  – Consistency checks were consistent with linear model and log-normal distribution assumptions.

• The optimized reconstruction parameters will enable future evaluation of various reconstruction strategies for MIBG SPECT.
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