Dictionary learning via regression: vascular MRI application

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Dictionary learning via regression: vascular MRI application

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Magnetic Resonance Fingerprinting (MRF)
Idea in the context of microvascularization

Magnetic Resonance Fingerprinting (MRF)

Principle

2-step procedure:

1. Dictionary design
   - Grid formation
   - MR signal simulations

2. Matching procedure
   - Distance computations
   - Estimation

Appeal of the MRF method: **fast, robust, accurate and flexible**

Limitations
Complex model and time-consuming simulation

The denser the grid, the more accurate the estimates

Typical dictionary size order:
\[ \approx 100^{\text{Nber of parameters}} \]

How to limit the growth of the dictionary while increasing the number of parameters?
Solve the inverse problem
High-to-low regression context

Find a way to reduce the dictionary sizes (keeping the estimation accuracy of MRF)

• Nearest-neighbor methods → [D. Ma, MRF (2013)]

• Dictionary learning = regression, characteristics:
  • Nonlinear
  • From high-dimensional space to low-dimensional space
Proposed solution: regression

High-to-low regression context

- Kernel methods and local regression $\rightarrow$ [G. Nataraj, \textit{PERK} (2017)]
- Neural Networks $\rightarrow$ [O. Cohen, \textit{DRONE} (2018)]
- Model inference $\rightarrow$ \textit{Proposed approach}

Gaussian locally-linear mapping (GLLiM)

- Solves nonlinear mapping problem automatically
- Solves the \textit{inverse problem}, then derives the \textit{forward model} parameters
Extremely fast and accurate estimation of 6 parameters while reducing the dictionary size by a factor > 60
Results

Real data

<table>
<thead>
<tr>
<th>Blood Volume fraction maps (%)</th>
<th>Analytical approach</th>
<th>Classic MRF estimates ($10^5$ signals)</th>
<th>Regression MRF estimates ($10^4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anatomical image</td>
<td></td>
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</tbody>
</table>
GLLiM has the advantage to provide a full posterior distribution, from this distribution we compute:

- the **mean** to obtain the **parameter estimation**
- the **standard deviation** to obtain a **confidence index** related to
Summary
Previous and future works

- Very fast computation of estimates
- Important dictionary size reduction factor
- Accurate estimates (both on synthetical and real data)

Work not presented:
  • Dictionary conception

Future work:
  • Compare with neural network regressions
  • Validate results with histology
References

MRF methods:
• Ma, Dan, et al., Magnetic resonance fingerprinting, Nature (2013)
• Nataraj, Gopal, Jon-Fredrik Nielsen, and Jeffrey A. Fessler, Dictionary-free mri parameter estimation via kernel ridge regression, ISBI (2017)
• Cohen, Ouri, Bo Zhu, and Matthew S. Rosen, MR fingerprinting Deep RecOnstruction NEtwork (DRONE), MRM (2018)

Simulation tool:
• Pannetier, Nicolas Adrien, et al., A simulation tool for dynamic contrast enhanced MRI, PloS one (2013)

Regression:

Data:
Thank you for listening

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