Deep Learning-based Magnetic Resonance Fingerprinting

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Who am I

• B.Sc. Medical Computer Science (OTH Regensburg)
  • Medical image segmentation
    with Prof. Dr. Christoph Palm

• M.Sc./Ph.D. Computer Science (FAU Erlangen-Nürnberg) in close collaboration with Siemens Healthineers, MR Predevelopment, Erlangen
  • Acquisition and reconstruction methods for Quantitative Magnetic Resonance Imaging
  • With Prof. Dr. Andreas Maier
Outline

1. Magnetic Resonance Imaging (MRI) Basics
2. Magnetic Resonance (MR) Fingerprinting
3. Deep Learning Basics
4. Deep Learning Approaches for MR Fingerprinting
5. Summary & Conclusion
Magnetic Resonance Imaging Basics
Magnetic Resonance Imaging

- Non-invasive imaging of soft tissues
Magnetic Resonance Imaging

- Uses hydrogen nuclei within the human body
- Strong magnet field $B_0$
Magnetic Resonance Imaging

Flip angle $\alpha$

Equilibrium state

Excitation state

$\alpha$ adds energy to the system.
Magnetic Resonance Imaging

Emits added energy

Relaxation state

Receiver coil

Signal
Magnetic Resonance Imaging

Emits added energy

Receiver coil

Signal

Relaxation state
**$T_1, T_2$ relaxation times**

- **Relaxation state**: described using two time constants
- $T_1$: Recovery of $M_z$ to reach $M_0$
- $T_2$: $M_{xy}$ diminishes

→ Depends on different tissue states

http://mriquestions.com/what-is-t1.html
http://mriquestions.com/what-is-t2.html
A variety of effects can be measured in MRI

- Spin density
- T1
- T2
- Oxygenation
- Temperature
- Chemical exchange
- Diffusion
- Flow
- Magnetization transfer
- $B_1^+$
- $B_1^-$
- $B_0$
MRI provides excellent soft tissue contrast ...

... but diagnosis is mostly based on 'hypo-intense' and 'hyper-intense'

→ Qualitative vs. Quantitative MRI
Conventional MR acquisition – weighted images
Quantitative MRI – parameter maps
Magnetic Resonance (MR) Fingerprinting
From Qualitative to Quantitative Imaging

$T_2$ weighted

$T_1$ relaxation [ms]

$T_2$ relaxation [ms]

Image courtesy of Dr Andreas Bartsch, Radiologie Bamberg, Universities of Heidelberg and Wuerzburg, University of Oxford.
MR Fingerprinting: General Approach

Randomized Acquisition
Different tissues look different

Pattern Recognition

Information
\( T_1 \)
\( T_2 \)
Water diffusion
Cellularity

Magnetic Resonance Fingerprinting is currently under development and not commercially available. It is not for sale in the U.S. Its future availability cannot be guaranteed.
MR Fingerprinting: Acquisition and Reconstruction
MR Fingerprinting: General Approach

- **MRF Dictionary**

- **T1 Map**

- **T2 Map**

- **Dictionary Matching**
Acquire the fingerprint with a special MRF excitation.

Magnetic Resonance Fingerprinting is currently under development and not commercially available. It is not for sale. Its future availability cannot be guaranteed.
MR Fingerprinting

Dictionary Generation

MRF dictionary

Magnetic Resonance Fingerprinting is currently under development and not commercially available. It is not for sale. Its future availability cannot be guaranteed.
MR Fingerprinting Matching

Match the fingerprint with an MRF dictionary

Acquired signal

Dictionary

Signal magnitude over time

Signal magnitude over time

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MR Fingerprinting
Map generation

Magnetic Resonance Fingerprinting is currently under development and not commercially available. It is not for sale. Its future availability cannot be guaranteed.

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MR Fingerprinting: Dictionary Matching

- Simple Pattern Matching (Inner Product Matching, IPM) \[^{[1]}\]
  - Comparison to pre-simulated dictionary with signals of possible parameter combinations

Selecting the maximum IP with corresponding quantitative parameters

Inner products of $m_s$ with whole dictionary $D: d_1 \ldots d_n$

Measured signal (one voxel) $m_s$

\[
IP_1 \ldots n = m_s \cdot d_1 \ldots d_n
\]

MR Fingerprinting: Dictionary Matching

- Fast Pattern Matching [1]
  - Clustering prior to IPM

Step 2: Inner products of $m_s$ with every signal in $g_{max}$ and selecting the maximum IP with corresponding quantitative parameters

Step 1: Inner products of $m_s$ with $g_{s1} \ldots g_{sm}$ and selecting the group $g_{max}$

Measured signal (one voxel) $m_s$

---

MR Fingerprinting: Dictionary Matching

- (Simple) pattern matching methods with simulated dictionary

Drawbacks:
- Discrete dictionary → erroneous maps [1]
  - Quantitative maps can be only retrieved from the parameters in the dictionary
- Resource limitations
  - Storage: New dimension? How many fingerprints? Which step sizes?
  - Time: Exhaustive search

MR Fingerprinting and Deep Learning

Replacing the pattern matching with Deep Learning
→ Predestinated for machine learning approaches
→ Continuous predictions
→ Efficient (time, storage)
Deep Learning Basics
What is Deep Learning?

- **Artificial Intelligence (AI):**
  (Automatic) machine learning approaches for intelligence behavior
What is Deep Learning?

• **Artificial Intelligence (AI):**
  (Automatic) machine learning approaches for intelligent behavior / pattern recognition

• **Deep Learning** is one field/area of AI methods
What is Deep Learning?

- **Artificial Intelligence (AI):** (Automatic) machine learning approaches for intelligent behavior / pattern recognition

- **Deep Learning** is one field/area of AI methods
  - Artificial neural networks
  - Deep networks → many layers
  - Systems learn from large amount of data
Artificial (Deep) Neural Networks: Structure

- Imitate the function of the neurons in human brain (in a very simplified form)

Structure of one layer:

- One network = multiple layers
- One layer = multiple neurons
- Neurons process information and pass it to the next layer
- Weights/operations are learnable
- More layers → more information can be extracted for the solution of complex problems

Artificial (Deep) Neural Networks: Application

Input data
e.g., medical images

Artificial (Deep) Neural Network

Output Data
e.g., segmented structures
Artificial (Deep) Neural Networks: Application

**Input data**
- e.g., medical images

**Artificial (Deep) Neural Network**
- Layers with neurons extract **relevant information and pattern** from data with mathematical operations (e.g., filter)
- Combination of these extracted information gives the desired output data

**Output Data**
- e.g., segmented structures

• Which pattern are relevant? – Learning from data during the training
Artificial (Deep) Neural Networks: Training

• The network has to learn which weights/operations to use for one specific application

• For this, a large data base with examples + ground-truth labels
  • E.g., Image + segmented structures

• The network learns to extract the relevant patterns from the given data, such that the patterns can be combined for the desired output
Artificial (Deep) Neural Networks: Training

• **Before training:**
  - Weights within network are random

• **Training:**
  - Data is forwarded through network, results are compared to ground-truth labels
  - Error is backpropagated and used to adjust weights in the correct direction

• **After training:**
  - Application of the network to new, unseen data (without ground-truth labels)
  - Generates new results
MR Fingerprinting: Deep Learning-based Reconstruction
First Steps
Back to 2017: First Steps [1]

Supervised regression + Convolutional Neural Network (CNN)

\[ y = f(x) \]

\( T_1, T_2 \) [\( ms \)]

Fingerprint (magnitude signal)

First Steps: Architecture [1]

- 3 convolutional layers (kernel: 3×3) + 1 fully connected layer
- Feature maps: 32 ... 128
- L2 loss function
- Gradient descent + Adam optimizer

First Steps: Experiments [1]

• Training on simulated fingerprints
  • “Simple” problem to solve
  • No artifacts, no noise → clear patterns

• Ground-truth: Fine-resolved dictionary covering representative human tissue values
  • $T_1$: 50 – 4,500 ms
  • $T_2$: 20 – 800 ms
  • Overall 120,000 fingerprints

First Steps: Results [1]

- Training on simulated fingerprints

\[ T_1 \text{ mean error } 1.6 \pm 1.56 \text{ ms} \]

\[ T_2 \text{ mean error } 1.18 \pm 0.92 \text{ ms} \]

- Small errors for fingerprints not used in training
- Network is able to learn pattern and to interpolate between them
- Continuous predictions are possible (interpolation between two fingerprints)

First Steps: Results [1]

Runtime on CPU (one fingerprint)

- Dictionary with 120,000 entries (runtime increases linearly to size)
- IPM: Inner Product Matching
- FGM: Fast Group Matching

<table>
<thead>
<tr>
<th>Method</th>
<th>$[ms]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPM</td>
<td>926.9</td>
</tr>
<tr>
<td>FGM (144 groups)</td>
<td>12.8</td>
</tr>
<tr>
<td>CNN (Ours)</td>
<td>8.9</td>
</tr>
</tbody>
</table>

**CNN on GPU: 1.5 ms**

Storage requirements

<table>
<thead>
<tr>
<th>Method</th>
<th>[MB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dictionary</td>
<td>3.728</td>
</tr>
<tr>
<td>CNN</td>
<td>1.02</td>
</tr>
</tbody>
</table>

→ Clear improvements

First Steps: Measured Data

- Training on simulated dictionary + testing on measured fingerprints

Phantom → Volunteer

$T_1$ $T_2$

→ Complete failure on "real" fingerprints
→ Strong influence from signal acquisition and undersampling
First Steps: Measured data

- Undersampling artifacts heavily corrupt true signals (here: Undersampling factor 48)
First Steps: Measured data

- “Different” signals for one set of parameters
- Artifacts residuum signals depend on spatial location and object geometry
- Signal in one voxel is mixed with signals from other voxels
First Steps: Measured data [1]

- Undersampling → “Ambiguity“ of signals for one parameter
- Extended architectures for measured data

First Steps: Measured data [1]

Train with human signals from transversal orientation (6 slices)

- Test on
  - Other transversal slices
  - Slices from other orientations

- Model used for training on simulated data (3 convolutional, 1 fully connected layers)
- Extended model (6 convolutional, 6 fully connected layers)

First Steps: Measured data [1]

Results: $T_1$ maps [ms]

**4 layers architecture**

$T_1$ mean error [ms]: 229 ± 215

**12 layers architecture**

$T_1$ mean error [ms]: 92 ± 167

IPM (ground truth)

CNN predicted

First Steps: Measured data [1]

Results: $T_2$ maps [ms]

4 layers architecture
$T_2$ mean error [ms]: 55 ± 58

12 layers architecture
$T_2$ mean error [ms]: 19 ± 44

First Steps: Measured data

Results: 12 layers model, other orientations ($T_1$ maps [ms])

- Big differences between artifacts from different orientations
- Bad generalization ability over different artifacts/orientations
First Steps: Lessons Learnt

- Pattern encoded in (clean) fingerprints can be easily detected with (simple) networks.
- Networks can interpolate between fingerprints and provide continuous predictions.
- Networks clearly outperform Dictionary Matching methods in terms of runtime and storage requirements.

- Strong undersampling lead to fast imaging, but the resulting artifacts are a **big challenge** for DL-based reconstruction.
Some Further Steps
Further Improvements

1) All components of complex signals [1]
   → Use the information from real and imaginary parts
2) Other architectures
   → Advanced architectures
3) Small data patches instead of one-pixel-fingerprint input
   → Neighbor voxels are similar, outlier robustness

RinQ Fingerprinting: Reconstruction using RNNs [1]

Combination of

- **Recurrent Neural Network** (RNN) architecture: Fingerprints are correlated in time and
- **Quantile layer**: Small spatial patches of voxels as inputs

RinQ Fingerprinting: Experiments [1]

RinQ Fingerprinting: Experiments [1]

Training and test data

- 12 transversal brain slices
- 4 volunteers (2 female, 43±15 years)
- MAGNETOM Skyra 3T scanner (Siemens Healthcare, Erlangen, Germany)
  Prototype sequence based on Fast Imaging with Steady State Precession and spiral readouts [2], variable TR (12-15ms), FA (5-74°), number of repetitions: 3,000, undersampling factor: 48
  Field-of-View: 300mm², resolution: 1.17×1.17×5.00mm³
- All slices randomly for training, validation and testing

Ground-truth data

- Fine-resolved dictionary with overall 691,497 signals for possible parameter combinations
- T₁: 10 – 4,500 ms, T₂: 2 – 3,000 ms
- Signals reduced to 50 main components in the time domain using SVD to be able to reconstruct relaxation maps in a reasonable time and memory consumption

RinQ Fingerprinting: Results [1]

CNN₁: CNN model with single-voxel inputs
RNN₁: RNN model with single-voxel inputs
RNN₃: RNN model with 3×3 spatial neighbor inputs

Sₘ: Magnitude signals
Sₐ: Complex-valued signals

→ Complex-valued inputs outperform magnitude inputs
→ RNNs outperform CNNs
→ RNNs with spatial inputs and quantile layer outperform RNNs without quantile layer

<table>
<thead>
<tr>
<th>Input signals</th>
<th>Validation loss [ms]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sm ∈ ℝ</td>
<td>636.96   424.96   -</td>
</tr>
<tr>
<td>Sc ∈ ℂ</td>
<td>470.26   269.20   221.52</td>
</tr>
</tbody>
</table>

RinQ Fingerprinting: CNN Results [1]

- Reduced errors with complex-valued signals
- Still heavy artifacts using CNNs

RinQ Fingerprinting: RNN Results [1]

- Reduced errors with complex-valued signals
- Improved reconstructed image quality, reduced heavy ringing artifacts

RinQ Fingerprinting: RNN + Quantile Layer Results [1]

Further improvement in comparison to RNNs without quantile layer
Noisy-less reconstructed image quality, preserved edges between different tissues

RinQ Fingerprinting: Lessons Learnt [1]

→ Complex-valued inputs outperform magnitude inputs
  • CNN: Errors reduced up to 62%, RNN more than 50%
  • Reduced corruption of the heavy ringing artifacts with complex-valued signals

→ RNNs outperform CNNs
  • Reduction of errors up to 53% compared to CNNs
  • RNN is capable of reconstructing high detail parameter maps

→ RNNs with spatial inputs and quantile layer outperform RNNs without quantile layer
  • Reduction of errors up to 57% compared to pure RNNs
  • Influence particularly evident at transitions between different tissue types

MR Fingerprinting Reconstruction: Cleaning the Fingerprints
Cleaning the Fingerprints?

- Undersampling artifacts heavily influence the DL performance
- Undersampling artifacts differ a lot between subjects, orientations or acquisition settings
- **But**: Clean (simulated-like) fingerprints are an “easy“ DL problem

→ Can we „clean“ measured fingerprints and use them for DL-based matching?
Cleaning the Fingerprints [1]

- Two-step DL approach:
  1) Artifact-affected fingerprints → clean fingerprints
  2) Clean fingerprints as input for a (lean) DL network

→ Artifact Reduction and Regression for MR Fingerprinting [1]

Cleaning the Fingerprints: Step 1 [1]

- U-Net architecture [2]
- Input: Whole slice (complex signals, compressed) → undersampling artifacts

Cleaning the Fingerprints: Step 2 [1]

• Using a simple CNN from our previous work [2]

Cleaning the Fingerprints: Data [1]

Training and test data

- 85 transveral brain slices
- 10 volunteers (5 female, 39.2±14.3 years)
- Split: 8/1/1
- 2 scanners: MAGNETOM Skyra, Prisma 3T (Siemens Healthcare, Erlangen, Germany)

Prototype sequence based on Fast Imaging with Steady State Precession and spiral readouts [2], variable TR (12-15 ms), FA (5-74°), number of repetitions: 3,000, undersampling factor: 48
Field-of-View: 300 mm², resolution: 1.17x1.17x5.00 mm³

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## Cleaning the Fingerprints: Experiments [1]

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Step 1</th>
<th>Step 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1)</td>
<td>---</td>
<td>CNN trained on uncleaned fingerprints</td>
</tr>
<tr>
<td>2)</td>
<td>Cleaned signals by U-Net</td>
<td>CNN trained on cleaned fingerprints</td>
</tr>
</tbody>
</table>

Can we clean the fingerprints with the U-Net, such the measured fingerprints are similar to the simulated and only use a simple second network for the regression?

---

Cleaning the Fingerprints: Preliminary Results [1]

T₁ GT

T₁ predicted

T₂ GT

T₂ predicted

T₁ GT-predicted

T₂ GT-predicted

Experiment 1:
- No U-Net for cleaning
- CNN trained on measured fingerprints

Cleaning the Fingerprints: Preliminary Results [1]

- Cleaned slices with decreased artifacts

Input | Output | GT | Error | Input | Output | GT | Error
--- | --- | --- | --- | --- | --- | --- | ---
(a) 1st component | (a) 1st component | | | (c) 20th component | (c) 20th component | | |
(b) 5th component | (b) 5th component | | | (d) 50th component | (d) 50th component | | |

Cleaning the Fingerprints: Preliminary Results [1]

Experiment 2:
- U-Net for cleaning
- CNN trained on cleaned fingerprints

Cleaning the Fingerprints: Lessons Learnt

• Clear improvement with “cleaned“ fingerprints
  • $T_1$: by 52%
  • $T_2$: by 51%

• Mapping from corrupted (measured) to clean (simulated-like) fingerprints is possible using Deep Learning
Deep Learning for MR Fingerprinting Now

• Ambiguity of different deep learning-based approaches (05/14/2020)
Summary & Conclusion
Summary & Conclusion

• MR Fingerprinting: One quantitative method with great potential
  • But: Slow and expensive state-of-the-art reconstruction

• Deep Learning is well suitable for MR Fingerprinting reconstruction
  • Fast
  • Accurate
  • Accelerating and shortening acquisitions

• „Clean“ fingerprints are a quite simple problem to solve for (simple) neural networks
• Influences during the scans make it much harder (artifacts, undersampling, noise)
Summary & Conclusion (II)

• Ambiguity of methods and different network architectures for especially two aims:
  • Preprocessing of fingerprints:
    • Artifacts reduction
    • Noise suppression
    • Compression
  • Pattern matching
• Combination of Deep Learning and conventional techniques

• Different inputs:
  • Whole slices
  • Single fingerprints
  • Complex or magnitude data
Summary & Conclusion (III)

• Challenges and open questions:
  • Simulations vs. in-vivo: Undersampling artifacts as the main challenge
  • Multi-dimensional input data → Compression needed
  • Dictionary: appropriate ground-truth maps?
  • Comparison of Dictionary Matching, DL and other quantitative methods?

• Generalization is still a problem
  • Different acquisition schemes/sequences
  • Different undersamplings
  • Different anatomies
  • Most work deals with one kind of settings
Thanks…

- Prof. Dr. Andreas Maier & PRL team

- Siemens Healthineers MR Fingerprinting Predevelopment in Erlangen, especially:
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Thank you!

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