Total Generalized Variation methods for Quantitative Susceptibility MR Mapping

Alessandra Bertoldo
Magnetic Susceptibility $\chi$: What is It?

- It is an intrinsic property of materials, including tissue.
- Determines how materials will behave in an applied magnetic field.
- It could be positive or negative:
  - Diamagnetic material have negative $\chi$-values.
  - Paramagnetic material have positive $\chi$-values.
  - Ferromagnetic materials have large $\chi$-values and may exhibit magnetization even in absence of applied fields.
Magnetic Susceptibility: Types and Origins

SUSCEPTIBILITY SPECTRUM

Region of "MRI Compatibility"

From Schenck, Med Phys, 1996
For isotropic (and non-ferromagnetic) materials, $\chi$ is defined by the linear relation:

$$\vec{M} = \chi \vec{H}$$

Magnetisation, i.e. magnetic moment per volume unit [A/m]

The total the magnetic induction $\vec{B}$ and the field $\vec{H}$ are related by:

$$\vec{B} = \mu_0 \left(\vec{H} + \vec{M}\right)$$

magnetic permeability of free space [A/m]
Magnetic Susceptibility: Types and Origins

Diamagnetism
\( \chi < 0 \)

\[ + \bar{M} \downarrow = \bar{B} \]

Water ~ -9 ppm
Bone ~ -8.4 ppm
Fat ~ -7.8 ppm

Paramagnetism
\( \chi > 0 \)

\[ + \bar{M} \uparrow = \bar{B} \]

Deoxyhaemoglobin in blood ~ +2.26 ppm
Dominant source of susceptibility variation in the brain is paramagnetic non-haeme iron.

Perl’s stain – Putamen; Caudate; Globus Pallidus

Drayer et al. AJR 1986; 147: 103–110.
Correlation of bulk magnetic susceptibility with measured iron concentration. The line represents the regression of all data points and the dotted lines indicate the 95% confidence intervals. [Langkammer et al, Neuroimage (2012), 62(3):1593-9]
Dominant source of susceptibility variation in the normal brain is paramagnetic non-haeme iron.

Also see the diamagnetic contribution from myelin.

Corpus Callosum, Optic Radiations

Michigan State University Brain Biodiversity Bank
Magnetic Susceptibility: MRI

Dominant source of susceptibility variation in the normal brain is paramagnetic non-haeme iron.

Also see the diamagnetic contribution from myelin.

And from paramagnetic deoxyhaemoglobin in venous blood.

Haemosiderin (paramagnetic) can be distinguished from calcification (diamagnetic).

QSM shows the active lesion with positive susceptibility (red arrow) of calcified lesions with negative susceptibilities (yellow arrows) in neurocysticercosis.

Quantitative Susceptibility Mapping (QSM) is an MRI technique sensitive to endogenous magnetic biomarkers such as:

- Iron
- Calcium
- Myelin

Applications in:
- Neurodegenerative diseases
- Multiple sclerosis
- Microbleeds measuring
Measuring $\chi$ in MR: Gradient Echo

$$|S(TE)| \propto e^{-TE/T_2^*}$$
Measuring $\chi$: Relationship with the GRE MRI Phase

$$S(TE) \propto e^{-\frac{TE}{T_2^*}} e^{i\phi}$$

$$\phi = \phi_0 - \gamma \Delta BTE$$

Diagram:
- $S$
- $G_x$
- $G_y$
- $G_z$
- RF
- TE
- TR
Measuring $\chi$: Relationship with the GRE MRI Phase

\[ S(TE) \propto e^{-\frac{TE}{T_2^*}} e^{i\phi} \quad \phi = \phi_0 - \gamma \Delta B_z TE \]

Field offset
RF phase
Measuring $\chi$: Relationship with the GRE MRI Phase

- To estimate $\Delta B$ and $\phi_0$ need measurements at multiple TE-values
- Measure single or multiple echoes per RF pulse

$\phi = \phi_0 - \gamma \Delta B_z T E$
Measuring $\chi$: Relationship with the GRE MRI Phase

- To estimate $\Delta B$ and $\phi_0$ need measurements at multiple TE-values
- Measure single or multiple echoes per RF pulse

$$\phi = \phi_0 - \gamma \Delta B_z TE$$

![Diagram showing sequence of events in GRE MRI with $S$, $G_x$, $G_y$, $G_z$, and RF pulses, followed by TE and TR intervals. A graph illustrates the relationship between $\phi$ and TE, with the slope yielding $\Delta B$.](image)
Overview

![Diagram](image)

- Inverse problem
- Magnetic susceptibility
- Forward problem
- Field perturbation
- Field perturbation estimate
- Phase of MR signal
- Background Field Removal
- Unwrapping
- Phase Measurement
- Image Processing
- MR Physics
Measuring $\chi$ from $\phi$: Pre-processing steps

1. Acquire $T_2^*$-weighted Gradient Echo Images
2. Unwrap the Phase
3. Remove Background Field Variations
4. Solve the Local Field-to-Susceptibility Inverse Problem

$\chi$
Measuring $\chi$ from $\phi$: Pre-processing steps

1. Acquire $T_2^*$-weighted Gradient Echo Images
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4. Solve the Local Field-to-Susceptibility Inverse Problem

$\chi$
Unwrap the Phase

- Phase needs to be unwrapped, to remove $2\pi$ jumps in phase.

\[
S(TE) \propto e^{-TE/T_2^*} e^{i\phi} \\
\phi = \tan^{-1}\left(\frac{Im(S)}{Re(S)}\right)
\]
Unwrap the Phase

Phase needs to be unwrapped to remove $2\pi$ jumps

Arctan is defined in $[-\pi, \pi)$ while the phase does not

Unwrapping involves adding an appropriate multiple of $2\pi$ to measured phase to eliminate discontinuities

Variety of approaches to unwrapping (real-space or Fourier domain)
Unwrap the Phase

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Measuring $\chi$ from $\phi$: Pre-processing steps

1. Acquire $T_2^*$-weighted Gradient Echo Images
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$\chi$
Measured field, $\Delta B$, is the sum of externally and internally generated fields:

$$\Delta B = B_{\text{ext}} + B_{\text{int}}$$

Only $B_{\text{int}}$ should be used in calculating $\Rightarrow$ Need to fill out $B_{\text{ext}}$

Fortunately they have different characteristics

<table>
<thead>
<tr>
<th></th>
<th>Bint</th>
<th>Bext</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnitude</td>
<td>Small</td>
<td>Large</td>
</tr>
<tr>
<td>Spatial Variation</td>
<td>Rapid</td>
<td>Slow</td>
</tr>
<tr>
<td>Harmonic</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Measured field, $\Delta B$, is the sum of externally and internally generated fields:

$$\Delta B = B_{ext} + B_{int}$$

Only $B_{int}$ should be used in calculating $\Rightarrow$ Need to fill out $B_{ext}$

Methods:

- Projection onto dipole fields
- SHARP and variants
- Laplacian boundary value (LBV)
- ......
Laplacian-based Methods (LBMs) removes the $\Delta B_{\text{ext}}(\vec{r})$ from the brain by recognising that:

$$\nabla^2 (\Delta B_{\text{ext}}(\vec{r})) = 0 \text{ for } \vec{r} \in \text{brain}$$

$$\Delta B_{\text{int}}(\vec{r}) = \nabla^{-2} \left( \nabla^2 (\Delta B(\vec{r})) \right) \text{ for } \vec{r} \in \text{brain}$$

$$\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}$$

three-dimensional Laplacian

Unwrapped phase

Local field

$\Delta B_{\text{ext}}$ removal algorithm
Measuring $\chi$ from $\phi$: Pre-processing steps

1. Acquire $T_2^*$-weighted Gradient Echo Images
2. Unwrap the Phase
3. Remove Background Field Variations
4. Solve the Local Field-to-Susceptibility Inverse Problem

$\chi$
Solve the Local Field-to-Susceptibility Inverse Problem

In image space ($\vec{r}$), we can calculate $\phi$ from $\chi$ by convolution with the unit dipole:

$$\Delta B_z(\vec{r}) = B_0 \cdot \chi(\vec{r}) \otimes D(\vec{r})$$

$D$ = dipole kernel in the $r$-space, assuming the main field oriented along $z$-direction

$$D(\vec{r}) = \frac{1}{4\pi} \frac{3 \cos^2(\theta) - 1}{r^3}$$

$$\phi = \phi_0 - \gamma \Delta B_z TE$$
In image space \((\vec{r})\), we can calculate \(\phi\) from \(\chi\) by **convolution** with the unit dipole:

\[
\frac{\Delta \phi(\vec{r}, \text{TE})}{\gamma B_0 \text{TE}} = \chi(\vec{r}) \otimes D(\vec{r})
\]

In image space, we can calculate \(\chi\) from \(\phi\) by **deconvolution** with the unit dipole:

\[
\chi(\vec{r}) = \frac{\Delta \phi(\vec{r}, \text{TE})}{\gamma B_0 \text{TE}} \otimes^{-1} D(\vec{r})
\]

- \(\chi\) magnetic susceptibility
- \(\gamma\) proton gyromagnetic ratio
- \(D\) magnetic dipole
- \(\text{TE}\) echo time
- \(B_0\) magnetic field strength
Solve the Local Field-to-Susceptibility Inverse Problem

In k-space ($\mathbf{k}$), the first relationship becomes a point-wise multiplication:

$$\frac{\Delta \phi(\mathbf{r}, \text{TE})}{\gamma B_0 \text{TE}} = \text{FT}^{-1} \left[ \text{FT} [\chi(\mathbf{r})] \cdot D (\mathbf{k}) \right]$$

**Forward problem**

$\Delta \chi \rightarrow \Delta \phi$

In k-space, the second relationship becomes a point-wise division:

$$\chi(\mathbf{r}) = \text{FT}^{-1} \left[ \frac{\text{FT} (\Delta \phi(\mathbf{r}, \text{TE}))}{\gamma B_0 \text{TE}} \cdot \frac{1}{D (\mathbf{k})} \right]$$

**Inverse problem (ill-posed)**

$\Delta \phi \rightarrow \Delta \chi$

$\chi$  magnetic susceptibility  $\gamma$  proton gyromagnetic ratio

$B_0$  magnetic field strength  $\text{TE}$  echo time

$\text{FT}$  Fourier Transform  $D$  FT of magnetic dipole

Solve the Local Field-to-Susceptibility Inverse Problem

In k-space ($\vec{k}$), the first relationship becomes a point-wise multiplication:

$$\frac{\Delta \phi(\vec{r}, \text{TE})}{\gamma B_0 \text{TE}} = \text{FT}^{-1} \left[ \text{FT}[\chi(\vec{r})] \cdot \left( \frac{1}{3} - \frac{k_z^2}{k_x^2 + k_y^2 + k_z^2} \right) \right]$$

Forward problem $\Delta \chi \rightarrow \Delta \phi$

In k-space, the second relationship becomes a point-wise division:

$$\chi(\vec{r}) = \text{FT}^{-1} \left[ \frac{\text{FT}(\Delta \phi(\vec{r}, \text{TE}))}{\gamma B_0 \text{TE}} \cdot \frac{1}{\left( \frac{1}{3} - \frac{k_z^2}{k_x^2 + k_y^2 + k_z^2} \right)} \right]$$

Inverse problem (ill-posed) $\Delta \phi \rightarrow \Delta \chi$

$\chi$ magnetic susceptibility $\gamma$ proton gyromagnetic ratio
$B_0$ magnetic field strength $\text{TE}$ echo time
$\text{FT}$ Fourier Transform

Solve the Local Field-to-Susceptibility Inverse Problem

\[
\chi(\vec{r}) = \text{FT}^{-1} \left[ \frac{\text{FT}(\Delta \phi(\vec{r}, \text{TE}))}{\gamma B_0 \text{TE}} \cdot \frac{1}{\left( \frac{1}{3} - \frac{k_z^2}{k_x^2 + k_y^2 + k_z^2} \right)} \right]
\]

\[
D(\vec{r}) = \frac{1}{4\pi} \frac{3 \cos^2(\theta) - 1}{r^3} = 0 \quad \Rightarrow \quad \theta = \pm 54.7^\circ \quad \text{Magic angle}
\]

Double cone surface of \(D(\vec{k})\) zeros

Issues:
divide by zero when \(D = 0\)
only know \(\Delta B_z\) inside the brain
Solve the Local Field-to-Susceptibility Inverse Problem

**Issues:**
- Divide by zero when $D = 0$
- Only know $\Delta B_z$ inside the brain

**Solution:**
- Threshold $D$ to limit magnitude of $1/D$

\[ |D(k)| = \left| \frac{1}{3} - (\hat{k} \cdot \hat{z})^2 \right| < \alpha \]
Solve the Local Field-to-Susceptibility Inverse Problem

Solve the Local Field-to-Susceptibility Inverse Problem

\[
\chi(\vec{r}) = \text{FT}^{-1} \left[ \frac{\text{FT}(\Delta \phi(\vec{r}, \text{TE}))}{\gamma B_0 \text{TE}} \cdot \frac{1}{\left( \frac{1}{3} - \frac{k_z^2}{k_x^2 + k_y^2 + k_z^2} \right)} \right]
\]

Inverse problem (ill-posed)
\[\Delta \phi \to \Delta \chi\]

\[
\hat{\chi}(\vec{r}) = \arg\min_{\chi} \left\| \frac{\Delta B_{\text{loc}}(\vec{r})}{B_0} - \text{FT}^{-1} \left( D(\vec{k}) \cdot \text{FT}(\chi(\vec{r})) \right) \right\|_2^2 + \lambda R
\]

Data fidelity term (least squares)

\[\lambda: \text{regularisation parameter}\]
\[R: \text{regularisation term (a function of } \|\chi\|_1 \text{ or } \|\chi\|_2\)
Solve the Local Field-to-Susceptibility Inverse Problem

\[ \hat{\chi}(\vec{r}) = \arg \min_{\chi} \left\| \frac{\Delta B_{\text{loc}}(\vec{r})}{B_0} - \text{FT}^{-1} \left( D(\vec{k}) \cdot \text{FT}(\chi(\vec{r})) \right) \right\|_2 + \lambda R \]

Double cone surface of \( D(\vec{k}) \) zeros

Shmueli et al, MRM, 2008

Less regularisation, more data fidelity
Measuring $\chi$ from $\phi$: Pre-processing steps

1. Acquire $T_2^*$-weighted Gradient Echo Images
2. Unwrap the Phase
3. Remove Background Field Variations
4. Solve the Local Field-to-Susceptibility Inverse Problem
Fast quantitative susceptibility mapping: The total generalized variation (TGV)

Inverse problem

Susceptibility sources → \textit{kernel} → Magnetic field inhomogeneities

Wrapped phase

MRI signal

Susceptibility map

Langkammer et al, Neuroimage. 2015 111:622-30
Fast quantitative susceptibility mapping: The total generalized variation (TGV)

The TGV functional itself represents a minimization problem:

\[
\text{TGV}_{\alpha_1,\alpha_0}^2(\chi) = \min_w \alpha_1 \|
\nabla \chi - w \|_M + \alpha_0 \| \varepsilon w \|_M
\]

\(\nabla\) denotes the gradient and \(\| \cdot \|_M\) the Radon norm (a generalization of the \(L^1\)-norm).
Fast quantitative susceptibility mapping: The total generalized variation (TGV)

\[ \text{TGV}^{2}_{\alpha_1, \alpha_0}(\chi) = \min_{w} \alpha_1 \| \nabla \chi - w \|_M + \alpha_0 \| \varepsilon w \|_M \]

\[ \varepsilon w = \left( \begin{array}{cc} \frac{\partial w_1}{\partial x} & \frac{1}{2} \left( \frac{\partial w_1}{\partial y} + \frac{\partial w_2}{\partial x} \right) \\ \frac{1}{2} \left( \frac{\partial w_1}{\partial y} + \frac{\partial w_2}{\partial x} \right) & \frac{\partial w_2}{\partial y} \end{array} \right) \]

TGV\(^2\) inherently balances locally the first and the second derivative of a function, as determined by the ratio of the positive weights \(\alpha_1\) and \(\alpha_0\).
Fast quantitative susceptibility mapping: The total generalized variation (TGV)
23 algorithms were compared:

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Input Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>TKD (provided)</td>
<td>Threshold-based k-space division (TKD) (28) with zeroes at ill-conditioned</td>
<td>LBV</td>
</tr>
<tr>
<td></td>
<td>regions (cone) in k-space, threshold = 0.19</td>
<td></td>
</tr>
<tr>
<td>CFL2 (provided)</td>
<td>Closed-form L2-regularized inversion (48)</td>
<td>LBV</td>
</tr>
<tr>
<td>MARTINOS WTV</td>
<td>Compressed sensing compensated QSM (54) with accelerated reconstruction</td>
<td>LBV</td>
</tr>
<tr>
<td></td>
<td>using alternating direction method of multipliers (ADMM) optimization</td>
<td></td>
</tr>
<tr>
<td>GRAZ TGV</td>
<td>Total generalized variation (TGV)-based method incorporating phase</td>
<td>RAW</td>
</tr>
<tr>
<td></td>
<td>unwrapping, background field removal, and dipole inversion in single</td>
<td></td>
</tr>
<tr>
<td></td>
<td>iteration (66)</td>
<td></td>
</tr>
<tr>
<td>GRAZ TGV L1</td>
<td>Total generalized variation (TGV)-based method (66) with additional L1</td>
<td>RAW</td>
</tr>
<tr>
<td></td>
<td>magnitude stabilization</td>
<td></td>
</tr>
</tbody>
</table>
### Who is the best?

<table>
<thead>
<tr>
<th>Institution</th>
<th>Methodology</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>JENA HEIDI</td>
<td>Hybrid algorithm based on Homogeneity Enabled Incremental Dipole Inversion (HEIDI) that solves three subdomain of k-space using different approaches, depending on conditioning: 1) well-conditioned k-space solved using unregularized LSQR; 2) critical part of k-space recovered by solving weighted total variation problem with priors derived from phase images; and 3) transition area derived from LSQR solution using denoising (53). Parameters defining three subdomains chosen to obtain optimal error measures relative to gold standard.</td>
<td>LBV</td>
</tr>
<tr>
<td>JENA SDI</td>
<td>TKD algorithm with extreme thresholding of the dipole kernel and underestimation compensation based on deconvolution point-spread function as in superfast dipole inversion (SDI) (67).</td>
<td>LBV</td>
</tr>
<tr>
<td>UCL TKD 1</td>
<td>TKD as in (14,67), that is, without zeroes inside k-space cone. Threshold of ( h = \frac{1}{6} ) used with no correction for ( \chi ) underestimation.</td>
<td>LBV</td>
</tr>
<tr>
<td>UCL TIK</td>
<td>Closed-form Tikhonov (Tikh) inversion as alluded to in (58) and mentioned in (1) as Tikhonov-regularized minimal norm solution. 1 had ( a = 0.0688 ) and no correction for ( \chi ) underestimation. 2 had ( a = 0.0588 ) and correction for ( \chi ) underestimation with a factor of 1.69. 4 had ( a = 0.029 ) and correction for ( \chi ) underestimation with a factor of 1.30.</td>
<td>LBV</td>
</tr>
<tr>
<td>JHU-XMU SFORKD</td>
<td>Based on structural feature-based collaborative reconstruction (SFOR) QSM paper in (58); simplified L2 regularization terms in M-step and S-step; added de-noising operation, k-space-based L1 solver, and HEIDI-like k-space combination.</td>
<td>LBV</td>
</tr>
<tr>
<td>JHU-XMU SFOR2</td>
<td>Based on SFOR QSM paper in (58); L1 and L2 regularized two-step reconstruction with regularization a priori extracted from magnitude and interm susceptibility maps. See winning approach in categories HHCP and SSIM.</td>
<td>LBV</td>
</tr>
<tr>
<td>CHILE TGV L2</td>
<td>Magnitude-weighted TGV. Uses L2 data fidelity term, spatially weighted by square of magnitude. First-order approximation of nonlinear term (89).</td>
<td>LBV</td>
</tr>
<tr>
<td>CHILE TGV NL</td>
<td>Nonlinear (NL) TGV result. Uses nonlinear data fidelity term, similar to Liu's nonlinear MEDI but with fast solver with alternating direction method of multipliers (ADM) and mixture of global and local solvers to deal with nonlinear equation.</td>
<td>LBV</td>
</tr>
<tr>
<td>CHILE NLD</td>
<td>Discretization of dipole kernel based on (70). Uses finite differences and DFT to achieve analytical solution in Fourier domain.</td>
<td>LBV</td>
</tr>
<tr>
<td>CHICAGO TGV</td>
<td>Dipole kernel defined in space by Green's function, integrating it for each voxel (71).</td>
<td>LBV</td>
</tr>
<tr>
<td>BEREKELEY STAR</td>
<td>Streaking artifacts reduction (STAR) via isolating and calculating strong susceptibility sources automatically, then large and small susceptibility values were reconstructed using two-level TV regularization approach (72).</td>
<td>LBV</td>
</tr>
<tr>
<td>VANC URC</td>
<td>LSQR solver (55) followed by weighted compressed sensing minimization. See winning approach in category RMSE.</td>
<td>LBV</td>
</tr>
<tr>
<td>IBR ITSWIM</td>
<td>Variable regularization threshold for inverse process/k-space improvement with binary mask including deep gray matter nuclei and veins used in iterative algorithm (73).</td>
<td>LBV</td>
</tr>
<tr>
<td>SMU MATV</td>
<td>Morphology-adaptive total variation (MATV) separates target susceptibility into smooth and non-smooth regions in which the latter are assigned smaller TV weights than smooth regions during dipole inversion (58). See winning approach in ROI accuracy category.</td>
<td>LBV</td>
</tr>
<tr>
<td>SMU MTKD</td>
<td>TKD with morphological priors (MTKD). Target susceptibility map is separated into smooth and non-smooth regions by exploiting morphological information. Gradient of target susceptibility map forced to be zero in smooth regions and to be gradient of TKD-reconstructed susceptibility map in non-smooth regions (74).</td>
<td>LBV</td>
</tr>
<tr>
<td>NY MEDI</td>
<td>Morphology-enabled dipole inversion (MEDI) method using Bayesian regularization approach that adds spatial priors from magnitude image (13,25).</td>
<td>LBV</td>
</tr>
<tr>
<td>NY PD</td>
<td>Solving objective of MEDI using primal-dual (PD) formulation of total variation and forward difference method for discretization (61).</td>
<td>LBV</td>
</tr>
<tr>
<td>NY TFI</td>
<td>The total field inversion (TFI) method simultaneously estimates background and local fields, preventing error propagation from background field removal to QSM (73).</td>
<td>RAW</td>
</tr>
<tr>
<td>PHILIPS DTV</td>
<td>Single-step QSM starting from wrapped raw phase using directional total-variation (DTV), with MP-RAGE as prior for estimating edges (78).</td>
<td>RAW</td>
</tr>
</tbody>
</table>

*LBV, Laplacian boundary value preprocessed phase; RAW, raw phase (for single step algorithms).

The algorithms are named to reflect the team's institution or location followed by an abbreviation related to the technique(s) exploited by each algorithm.

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**Langkammer et al**

### Quantitative susceptibility mapping: Report from the 2016 reconstruction challenge.

<table>
<thead>
<tr>
<th>RMSE (%)</th>
<th>HFEN (%)</th>
<th>SSIM (0–1)</th>
<th>ROI Error (ppm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>69.0 VANC UBC</td>
<td>63.5 JHU-XMU SFCR2</td>
<td>0.94 JHU-XMU SFCR2</td>
<td>0.016 SMU MATV</td>
</tr>
<tr>
<td>70.3 JHU-XMU SFCR2</td>
<td>68.8 GRAZ TGV L1</td>
<td>JHU-XMU SFCR2</td>
<td>NY PD</td>
</tr>
<tr>
<td>73.6 MARTINOS WTV</td>
<td>68.9 VANC UBC</td>
<td>0.93 NY MEDI</td>
<td>0.017 CHILE TGV NL</td>
</tr>
<tr>
<td>74.2 PHILIPS DTV</td>
<td>70.9 PHILIPS DTV</td>
<td>GRAZ TGV</td>
<td>CHILE NLD</td>
</tr>
<tr>
<td>74.6 GRAZ TGV L1</td>
<td>71.8 SMU MATV</td>
<td>0.87 GRAZ TGV L1</td>
<td>SMU MTKD</td>
</tr>
<tr>
<td>75.2 UCL TIK 1</td>
<td>73.1 UCL TIK 1</td>
<td>0.84 CHILE TGV L2</td>
<td>0.018 CFL2</td>
</tr>
<tr>
<td>76.6 UCL TKD 1</td>
<td>73.6 MARTINOS WTV</td>
<td>NY TFI</td>
<td>UCL TIK 2</td>
</tr>
<tr>
<td>77.5 GRAZ TGV</td>
<td>74.1 IBR ITSWIM</td>
<td>0.83 JENA HEIDI</td>
<td>UCL TIK 4</td>
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<tr>
<td>BERKELEY STAR</td>
<td>74.2 JHU-XMU SFCR2</td>
<td>CHILE NLD</td>
<td>JHU-XMU SFCR2</td>
</tr>
<tr>
<td>79.1 SMU MATV</td>
<td>GRAZ TGV</td>
<td>CHILE TGV NL</td>
<td>CHILE TGV L2</td>
</tr>
</tbody>
</table>

HFEN, high-frequency error norm; RMSE, root mean squared error; SSIM, structure similarity index.
QSM: clinical impact

Data acquisition

- 3D GRE
- 10 echoes
- 320x256x64 matrix with R=2
- 0.8x0.7x3mm³ resolution
- TR 50ms
- Scan time 5 min
- All manufacturers can create complex GRE data in DICOM
Quantitative susceptibility mapping as an indicator of subcortical and limbic iron abnormality in Parkinson’s disease with dementia

Darrell T.H. Li\textsuperscript{a}, Edward S. Hui\textsuperscript{a}, Queenie Chan\textsuperscript{b}, N. Yao\textsuperscript{c,d}, S.E. Chua\textsuperscript{d,e}, Gráinne M. McAlonan\textsuperscript{d,f,g}, Shirley Y.Y. Pang\textsuperscript{h}, S.L. Ho\textsuperscript{h}, Henry K.F. Mak\textsuperscript{a,i,j,k}

\textsuperscript{a} Department of Diagnostic Radiology, The University of Hong Kong, Hong Kong,
\textsuperscript{b} Philips Healthcare, Hong Kong,
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Quantitative Susceptibility MRI to Detect Brain Iron in Amyotrophic Lateral Sclerosis

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High-resolution QSM for functional and structural depiction of subthalamic nuclei in DBS presurgical mapping

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A robust multi-scale approach to quantitative susceptibility mapping

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A robust multi-scale approach based on non-regularized variable kernels sophisticated harmonic artifact reduction for phase data for quantitative susceptibility mapping

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Quantitative susceptibility mapping using deep neural network: QSMnet

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QSM: potential clinical applications

1. Guiding Deep Brain Stimulation (DBS) in movement disorders
   Better visualization of the STN- accurate DBS electrode placement

2. Monitoring iron chelation therapy in Parkinson disease

3. Monitoring smoldering inflammation in Multiple sclerosis lesions
   Biomarker of MS chronic inflammation (innate)

4. Detecting Gad enhancing Multiple Sclerosis lesions

5. Diagnosis of neurodegenerative disorders, including multiple sclerosis: central vein, iron rims

6. Measuring microbleed burden in traumatic brain injury
ACKNOWLEDGEMENTS

Prof. Karin Shmueli, UCL, London, UK
Emma Biondetti, UCL, London UK

Prof. Richard Bowtell, University of Nottingham, UK

Agnese Tamanti, University of Verona, Italy
Alessandro Palombit, University of Padova, Italy
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NMR in Biomedicine special issue on MRI phase contrast and QSM:
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